The Impact of Environmental Subsidy on Adoption and R&D Environmental Investment*

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Abstract

This article is an empirical evaluation of the effects of a public environmental subsidy for technology adoption on environmental adoption (direct effect) and R&D investment (indirect effect), in a sample of Dutch non-service private companies over the 2006-2009 period. Combining information from surveys on the firm production and environmental costs, and by means of a continuous treatment matching approach, we are able to identify, for several subsidy amounts, whether an increase in such amounts may raise the levels or first differences in environmental technology adoption and R&D investment. We find negligible or significant crowding-out effects for both types of environmental investment, when controlling for firm invariant unobservables. Thus, our findings appear to suggest a serious re-modulation of the public policy tool under analysis, in terms of both the amounts provided and the firms targeted.

JEL Classification: H23, O32, O38, Q55.

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1 Introduction

Governments across the globe have been enacting a number of environmental policies aimed at managing climate change and preventing environmental disasters. Since the 1990s, environmental policies have become stricter virtually everywhere, with predictable differences between the most severe policies implemented in the Nordic countries and in the Netherlands, the feeblest in Greece and in Ireland, and those that are average, such as those in the UK and the US, which are near the OECD average (Albrizio et al., 2014). Through such policies, governments distribute a considerable quantity of public resources to support the adoption of the existing abatement technologies, either through tax policy or direct subsidies. Despite the magnitude of environmental public expenditure and its crucial role in addressing well-being and sustainability objectives, there is minimal empirical evidence concerning the impacts of government subsidies on clean technology adoption. Understanding whether public resources are effectively allocated is critical in modern economies whose governments aim to optimize the use of public spending, particularly in a time of tight public budgets, and to establish challenging policy targets relative to both the allocation of public spending and environmental matters. Therefore, analyzing the extent of the economic payoff of public financing to private companies' environmental investments becomes a definite major policy issue. Indeed, resources made available through a system of direct subsidies may result in an opportune use of public expenditure. Moreover, an efficient allocation of government financial support requires an analysis of the conditions under which the public intervention is expected to be most effective (Jacob and Lefgren, 2011).

In this article, we utilize a matching technique to identify the causal effect of receiving a subsidy for clean technology adoption on the subsequent environmental investments, in a sample of Dutch non-service plants. The objective of this policy tool is to encourage companies to implement environmental investments in their business operations such that (i) the use of an environmental friendly technology is involved; (ii) the chosen technology continues to have a small market share in relation to the alternative dirty technology; (iii) the alternative is more expensive than the environmentally unfriendly alternative dirty technology; and (iv) the investment is implemented in the Netherlands. The aforementioned policy requirements are clearly aimed at influencing the displacement of the incumbent technology by affecting how rapidly and deeply environmental technology diffuses and thus, favoring the process of formation and the development of abatement technology before it achieves the level of maturity; this is necessary to challenge and eventually substitute the current dirty technology paradigm (Grin et al., 2010; Jaffe et al. 2005; Elzen et al., 2004).

In doing so, policy makers recognize the complementarity between environmental policy and technology policy, which is well rooted in the contemporary academic debate (Acemoglu et al., 2012; Aghion et al., 2009; Arimura et al., 2007; Jaffe et al., 2005; Jaffe et. al., 2002; Henderson and Newell, 2011; Popp and Newell, 2012). At this nexus, scholars have begun to devote particular attention to the evaluation of such policies. Specifically, until now, a limited but growing literature has investigated the effects of environmental policy on the diffusion of clean technology in the private energy sector. The conclusions that can be derived from this body of research points to positive and relevant effects of environmental policy on the adoption of abatement technologies, and green-targeted R&D projects (Popp et al., 2010) as well as the adoption spillovers in the economy (Goulder and Parry, 2008). However, there remains minimal formal guidance on how to establish the optimal dose of environmental subsidies in the presence of firms that perform heterogeneous levels of private environmental investments. More precisely, two major questions are highlighted. First, what is the optimal amount of policy resources that policy makers must allocate by means of environmental subsidies? Second, do environmental subsidies for clean technology adoption also induce indirect effects on the research profile of the financed companies? Although applied economics offers a wide set of analytical instruments for the study of economic and welfare consequences of all sorts of government policies, to the best of our knowledge, no systematic empirical attempts have been implemented to assess the indirect impacts of environmental subsidies.

Environmental R&D activities present fundamentally different features from mere environmental technology adoption, because R&D investments are typically highly intangible and more risky, particularly for early-stage research activities, which are further from immediate commercialization. These different characteristics help to explain why governments need to target these activities with a mix of policy tools. However, grants that aim to finance the adoption of existing abatement technology can affect the wide range of the activities involved in the eco-innovation process. Firms' environmental R&D investments may occur not only through the stimulus of direct R&D subsidies, but also via learning effects through the utilization of new (publicly financed) abatement technology. Thus, encouraging clean technology adoption may eventually also be beneficial to environmental innovation (Fisher and Newell, 2008). If this is the case, the support to environmental investment may be considered as a scheme potentially attractive scheme for decision makers in addition to other market-based instruments such as direct R&D policies.

We analyze the aforementioned issues using a continuous treatment matching method (Hirano and Imbens, 2004; Bia and Mattei, 2008), which allows us to match enterprises that are exposed to a specific "dose" of treatment (i.e., amount of environmental subsidy) with companies that are similar in all their observable characteristics, except in the dose of treatment received. Consequently, we are able to compare financed companies with others that received a marginally lower amount of public resources. This allows the computation of the effect of a marginal variation in the dose of treatment on the outcome variable. As argued by recent empirical works, the main problem regarding the empirical evaluation of public grants to private environmental investments consists in having a better understanding of how the modulation of public financing affects the environmental outcome under study (Marino et al., 2015; Hottenrott, 2015; Görg and Strobl, 2009). Indeed, when evaluating the impact of a public subsidy on firms' environmental investments, it is reasonable to suppose that it is not only the provision of the subsidy, but also its amount that may matter (Marino et al., 2015).

Incorporating these aspects into any environmental policy analysis is essential. This assertion requests for an econometric approach that overcomes the commonly used binary treatment framework, which exploits information concerning the status of being subsidized (treated) or not (untreated). The wide use of the methodologies that are based on binary treatments, which estimate the average effect of the treatment, is justified by the fact that information on the amount of treatment received is rarely available in the commonly used environmental cost surveys. Thus, if data on the amount of treatment received is available, the perspective of an analysis based on continuous treatment matching is opened. Policy evaluations based on continuous treatment matching are scant (Marino et al., 2015; Hottenrott et al.; 2015) and, to the best of our knowledge, do not exist in the field of environmental policy. A major strength of our study is that we are able to identifying the exact amount of public environmental subsidies received by private firms, and to implement continuous treatment matching to evaluate the response pattern of environmental R&D investments in relation to the amount of the environmental subsidies received. This provides the possibility to express more precise policy recommendations; continuous treatment matching, in fact, allows making statements not only on the effectiveness of environmental subsidies, but also on their optimal amount. Additionally, we test the presence of cross-scheme effects, assessing whether indirect effects on environmental R&D investments exist.

Previous studies that investigate the effects of environmental subsidies generally did not distinguish between technology adoption and environmental R&D activities. This is partly due to a lack of simultaneous access to information on the volume of private investments that firms allocate to each of these activities. To tackle these issues, we use detailed information on private non-service companies contained in the Dutch Production Survey and Environmental Cost Survey,[1] during the 2006-2009 period. The latter survey reveals information concerning individual companies relative to their environmental performances and includes the amount of environmental subsidies firms receive from the government for the adoption of cleaner technologies.

Our outcome variables are both the level and first differences in the total environmental investments (subsequently, split into end-of-pipe and process-integrated environmental investments) and environmental R&D investments (split into intramural and extramural environmental R&D investments). When examining the outcome variables in first differences, we are able to tackle any potential bias due to time-invariant firm-

[1] The focus on companies in non-service industries permits us to assess the effectiveness of the policy tool under study for energy and carbon intensive firms, because the energy and manufacturing industries are the major contributor to GHG emissions around the world.

specific factors, that if not adequately considered, may lead to biased estimates. Our findings appear to suggest a re-modulation and better targeting of the public environmental subsidy under analysis. In fact, negligible or significant crowding-out effects are found for both technology adoption and R&D environmental investment, taken in first differences. Regarding the direct effects,it turns out that the substitution between private and public resources (or crowding-out) more likely occurs for the process-integrated rather than for the end-of-pipe environmental investment. Concerning the indirect effect, we find nearly negligible substitution effects for the internal environmental R&D investment but non-negligible effects for the green R&D performed externally.

The reminder of this paper is as follows: we review the related literature in Section 2, a brief description of the methodology is reported in Section 3, details on data and variables are provided in Section 4, results are discussed in Section 5, and we conclude in Section 6.

2 Literature review

One can easily find any field of economics that has been concerned with policy evaluation analysis as much as environmental economics. Inspired largely by the need to understand how to optimize the public budget allocation, the assessment of environmental technology policy has stimulated much empirical research. To address the inquiry relative to the environmental subsidy effectiveness, researchers typically utilize casual analyses based on counterfactuals, which address the issue of how firms would have acted in the absence of the policy intervention. The conceptual pillar on which these analyses are based is the recognition that firms that have applied for public grants may not be considered as randomly selected and therefore as representative of the entire underling population. Instead, firms' decisions are the result of the policy design, because firms are often well informed regarding the rules and standards of judgment that governmental authorities adopt to distribute public financial aid (i.e., self-selection).

There is growing empirical literature on the impact of environmental/technological policy on clean adoption (Allan et al., 2014). Most of these studies do not only regard direct subsidies, but also concern other policies, such as regulations. Earlier studies have typically found a positive and statistically significant effect of the policy under analysis on environmental adoption. Popp (2010) found that the adoption of NOx-control technologies on a sample of US coal fired power plants is driven by regulatory emission limits. Del Río González (2005) found that the effect of policy is particularly important for smaller firms. Arvanitis and Ley (2013) explored the determinants of eco-adoption on a sample of Swiss firms, finding that the adoption process depends on firm characteristics. Therefore, these studies seem to suggest that policy actions to stimulate green adoption may take into account the heterogeneity of firms and, hence, be designed depending on the characteristics of recipient companies.

Certain studies disentangled the effect of green policy on the adoption of green technologies by type of technology adopted: "end-of-pipe" or "process-integrated" technology. An end-of-pipe technology is applied in the last segments of the production process, to directly decrease the negative environmental externality (for instance, a pollution filter). A process-integrated technology is embedded in the production process, to modify its internal working in a greener manner (a new machinery that consumes less energy). A common finding from this stream of literature is that process-integrated technologies appear to be better supported by market-based policy instruments (technology subsidies), whereas end-of-pipe technologies are more command-and-control-regulation-driven (Frondel et al., 2007; Horbach et al., 2012).

The existing policy evaluations in this field of study are merely based on a single treatment framework. To the best of our knowledge, there are no empirical inquiries on the optimal amount of public environmental incentives (continuous treatment matching), but only concerning certain levels of policy stringency. This is due to the extensive use of innovation surveys as the most commonly used data source for measuring private companies innovation/adoption behaviors. These surveys collect evidence on the innovative strategies and outputs of companies. Despite their crucial role in collecting relevant firm level data, unfortunately, these surveys generally offer few insights into environmental innovation (Veugelers, 2012). Typically, information on public subsidies for environmental investment is scant and, when available, researchers are informed solely on the grant provision.

Porter and van der Linde (1995) stated that a more stringent policy enhances a higher level of green innovation and adoption.[2] Lanoie et al. (2011), in their analysis on the Porter Hypothesis, confirmed this assertion. Kerr and Newell (2003) analyzed the adoption of clean technologies in US refineries under different policy regimes. They found that adoption increases as policy stringency increases. Popp (2006) explored how regulatory stringency affects the adoption of SO2 and NOx abatement technologies across countries (US, Japan and Germany): his results indicate that the adoption of these technologies responded only to domestic environmental regulatory pressure, but not to foreign one. Frondel et al. (2007) found no impact of market-based instruments (eco-taxes and subsidies) on green adoption. The researchers explained their result as a consequence of a lax implementation of these policy tools.

Among studies that pertain to the Netherlands, Van Leeuwen and Mohnen (2013), using a panel data set

[2]Porter (1991) contradicted the traditional paradigm according to which environmental policy would impose additional costs on firms. He argued that "strict environmental regulations do not inevitably hinder competitive advantage against rivals; indeed, they often enhance it" (Porter 1991, 168). Subsequently, Porter and van der Linde (1995, 98) described pollution produced by companies as the result of inefficient processes that waste resources. Therefore, any action that aimed to reduce the pollution emissions may lead to an improvement in the productivity of the activities with which the wasted resources are exploited. Additionally, the researchers described more stringent but properly designed environmental regulations (in particular, market-based instruments such as taxes or cap-and-trade emissions allowances) as "trigger innovation [broadly defined] that may partially or [in some instances] more than fully offset the costs of complying with them."

of Dutch companies and implementing a structural model, that was first proposed by Crépon, et al. (1998), found support for the weak version of the Porter Hypothesis, given the positive effect of Dutch environmental subsidies on a firm's green R&D expenditures and green investments (the latter being differentiated between process-integrated and end-of-pipe).

3 Methodology

In this section, we briefly present the estimation methodology that is implemented in our empirical assessment of the Dutch environmental support policy. We deploy a continuous treatment approach, which appears to be extremely useful when the treatment doses are available and the their distribution is smooth enough across treatment levels. In fact, the latter may improve the precision of the inferences (Imbens and Wooldridge, 2009). The key assumption behind this estimation strategy is the so-called "weak unconfoundedness" introduced by Imbens (2000). Different from the conditional independence assumption (CIA) due to Rosenbaum and Rubin (1983) in the binary case, here the pairwise independence of the treatment with each of (not joint) the potential outcomes is solely required. Thus, the problems of bias removal and drawing causal inferences can be solved by adjusting for pre-treatment differences. In this setting, the computation of the conditional probability of receiving a specific level of treatment (not simply receiving it) given the pre-treatment observables is called the general propensity score (GPS). Because the weak unconfoundedness given all pre-treatment variables implies weak unconfoundedness given the GPS, the average treatment effects can be obtained by conditioning solely on the GPS (Hirano and Imbens, 2004). We compute the GPS by using all pre-treatment firm characterstics available in our data set (refer to next section for the description of such variables). We refer the reader to Bia and Mattei (2008) for further details on the implementation of this method.

Although the longitudinal dimension of our sample is very short, it partially allows us to combine the continuous matching with the DiD approach to make the unconfoundedness assumption less restrictive. The basic idea is that, although the unconfoundedness does not hold, it may be reasonable to assume that the evaluation bias is constant over a two year period. Thus, we evaluate the effect of the treatment on the difference in the outcome variable rather than on its level, thereby correcting for (relatively) time-invariant firm characteristics. A general drawback of matching analyses has roots in the nearly impossible exact identification of the decision rule adopted by public authorities. Therefore, the typical omitted variable issue could arise because we may miss variables (in our data set) that public authorities use for the attribution of the subsidies. However, in our analysis, we control for a set of relevant variables that definitely influence the public provision of environmental public subsidies and that are likely related to the aforementioned unobserved factors.

4 Data

The following section describes both the data sources and variables used in our empirical analysis and reports the main descriptive statistics concerning our final sample.

4.1 Data sources

The empirical analysis proposed in this paper utilizes a comprehensive data set obtained by collecting data on Dutch companies for the period 2006-2009. These data were obtained from the combination of two surveys: the Production Cost Survey (PS) and the Survey on Environmental Costs of firms (ECF).

The Production Statistics Survey (PS) contains firm-level data on capital assets, turnover, the value added, the export status, subsidies other than eco-subsidies, and the 2 digit industry code. We combined the production survey data and the environmental cost information based on the firms' unique common identifier. The Survey on Environmental Costs (ECF) collects relevant data on firm-level environmental activities in the 2006-2009 period. Specifically, the survey provides information (amongst others) on two types of environmental investments ("end-of-pipe" investment and "process-integrated eco-investment"), environmental subsidies for clean technology adoption and expenses on environmental R&D. The public environmental funding variable provides detailed information on the total amount received. Despite the fact that this survey is the principal data source of our research, it solely covers companies in non-service industries. This limits our empirical analysis to this branch of the economy. The combination of these two surveys has resulted in a sample with a short time dimension, which contains a total of 1,849 firm-year observations.

4.2 Variables

The available data allows us to control for several characteristics, which likely influence the public provision of a specific amount of policy treatment. Specifically, our set of pre-treatment variables includes the following: the *log of employment*; the *log of capital stock*; the *R&D intensity* measured as the ratio between R&D expenditure and firm size; the *environmental investment intensity*, which is the overall environmental investment scaled to the firm size, the dichotomous variables, which indicating whether the recipient is an *exporting* firm or benefits from other subsidies (*subsidy type1, 2 and 3*), respectively; the threshold size ($< 10, 10 - 49, 50 - 99.$ $100 - 499 > 499$) and the *2-digit industry* dummies. The inclusion of the capital stock and employment variables may highlight differences in the technologies exploited by the companies in their production process. Companies that present higher levels of capital assets may rely more heavily on the energy use than labor-intensive firms do. However, if the policy maker's intention is to support primarily capital-intensive companies, labor-intensive companies may be disadvantaged; thus, high reported values for capital assets may be positively associated with the amount of the environmental subsidy. Environmental and R&D investment intensity are also measures that may seriously affect the public provision of subsidies for environmental purposes, i.e., more environmental friendly and research-oriented companies may be able to attract larger funds when the public authorities expect higher (direct and indirect) returns to their financing. Apparently, innovative and eco-friendly firms operate in highly competitive environments, which promotes a sustainable growth and gain a competitive advantage by offering customers greater value. The same line of reasoning applies for the dummy variable that captures whether a firm is involved in the international arena by exporting its goods. Exporting firms are indeed characterized by higher productivity levels with a larger potential for innovation (Bernard and Jensen, 1999; Melitz, 2003). Moreover, threshold size and industry dummies are included to account for firm size group-specific effects and industry heterogeneity in the treatment dose.

The treatment variable is the *log of environmental subsidy*, which, similar to all monetary variables, is deflated by using the GDP deflator for the Netherlands in the year 2000. We retrieved the deflator from the World Development Indicators, the well-known United Nations online database. We log-transformed the environmental subsidy to smooth its distribution without losing any observation because we focus on the set of recipient firms, i.e., our sample does not include non-financed companies.

Our outcome variables refer to environmental investment either for technology adoption or R&D, which we split into (i) process-integrated and end-of-pipe or (ii) extramural and intramural investment, respectively. All outcomes are not log-transformed because such variables may take on the value 0. The distinction between adoption and R&D environmental investment helps us in disentangling the direct from the indirect effects of the public green subsidy, whereas the split (i) and (ii) may allow us to better identify which type of investment is more affected by the policy intervention.

4.3 Descriptive statistics

Table 1 reports the main descriptive statistics (mean and standard deviation) of treatment, outcome and pre-treatment variables. As noted earlier, our sample is composed of 1,849 observations over the 2006-2009 period. We observe a firm for at least two consecutive years, and because we exploit pre-treatment information, this implies that we use our treatment variable solely for the 2007-2009 time-span. Our treatment variable is reported both in levels and log-levels, its average value is approximately 22.5 thousand euros (EUR). The amount of technology adoption and R&D environmental investment is on average approximately 181 and 53 thousand EUR, respectively. The latter is for its four fifth (one fifth) composed of internal (external) R&D investment, whereas the former consists of 39 (61) percent of the process-integrated (end-of-pipe) investment. More closely examining the outcome variables in first differences, it turns out that companies seem to reduce their technology adoption and R&D environmental investment over time. Because these numbers are average values, they may not lead to any conclusion regarding potential crowding-out (substitution) or additionality behavior among differently treated firms. Indeed, this might just reflect a reallocation of firms' internal resources during the economic crisis that occurred in most of the sample period.

Examining our control variables, we find that the average capital stock is approximately 700 thousand EUR and that the average firm workforce is composed of 76 workers, although about half of the firms falls in the size category $10-49$. This evidence finds justification in the Dutch industrial structure, dominated by small and medium enterprises (Marsili and Verspagen, 2002). It also emerges that the average firm invests around 2 thousand EUR per worker in total environmental investment, whereas about half of this amount is devoted to green R&D. Approximately the 22 percent of the observations are related to exporting firms and a large share of the traced companies benefit from other public subsidies.

5 Results

Our results are reported in Table 2-7 or, alternatively, in Figure 1-12. Each table (or couple of figures) report the impact (i.e., treatment effect) of the amount of environmental subsidy (i.e., treatment dose) on a firm's outcome (i.e., response). The tables present similar layout: the first two columns show treatment doses both in level and log-levels; and column 3-5 (6-8) display the average treatment effect, its standard deviation and t-statistic for each associated dose when the outcome variable is taken in levels (first differences). Specifically, we report 9 treatment doses (from 1,000 to 54,600 EUR).[3] Treatment effects refer to a dose increase of 1,000 EUR. Figures report treatment doses on the x-axis and treatment effects on y-axis. Whereas figures help in the interpretation of the overall pattern associated with the treatment doses, tables ease the quantitative comparison of effects between the outcome variables in levels and first differences.

The impact of the green subsidy on the total environmental investment for adoption (i.e., the direct effect) is shown in Table 2. We generally observe non-significant (at the usual threshold levels) effects of the public subsidy when this outcome variable is taken in levels. Exceptions are very low doses and median doses, which are respectively associated with negative and positive effects, respectively. Specifically, it appears that, for recipients of approximately 1,000 (7,400) EUR, an increase of 1,000 EUR may induce a reduction (increase)

[3] We are aware that doses are not particularly large, however subsidies higher than 54,600 EUR represent less than the top 5% of the treatment distribution. In addition, recipients of such doses may barely be matched to counterfactuals (lower or higher subsidy recipients with similar pre-treatment characteristics).

in their environmental investment of 384 (242) EUR. However, if we examine the treatment effects for the same outcome variable in first differences (i.e., if we remove the unobserved two-year-invariant firm-specific component that may potentially correlate with the observables and therefore bias our estimates), we find that the substitution of private environmental investment with public resources appear to dominate, although significant at 10 percent level solely for medium-large (7,400-20,000 EUR) treatment doses. For this subset of recipients, an increase of 1,000 EUR in the dose may decrease the difference between the current and past environmental investment of 789-2,091 EUR. Table 3 and 4 report the treatment effects on process integrated and end-of-pipe environmental investment, respectively. This distinction allows us to evaluate the potential treatment effect heterogeneity between investment types and seemingly suggest a better design of the public policy tool in object. Relying primarily on the findings associated with the outcome in first differences, it turns out that the substitution between private and public resources more likely occurs for the process-integrated rather than for the end-of-pipe environmental investment. Significant substitution effects range from 260 to 2,600 EUR for the former, whereas for the latter we find significant negative effects being between 265 and 465 EUR and associated with lower doses.

Although no reliable evidence of any positive direct effect (i.e., additionality) of the public environmental subsidy is found, we here briefly report the indirect effects of the public environmental subsidy, i.e. the impact of such a subsidy on the R&D environmental investment. Again, we find different effects when comparing the analysis in levels to the one in first differences. Examining the treatment effects on levels, it seems that the subsidy significantly stimulates R&D activities - except for small doses (i.e. below 2,700 EUR) - independent of whether it is performed in-house or externally. However, these findings are not confirmed in the analysis in first differences, which actually show nearly negligible substitution effects for the internal environmental R&D investment but non-negligible ones for the complementary part. Specifically, a 1,000 EUR increase in the dose may induce a reduction in the difference between current and past external environmental R&D investment of 39-146 EUR for doses between 7,400 and 20,000 EUR.

Overall, the findings of our empirical exercise appear to suggest a re-modulation and better targeting of the public environmental subsidy under analysis. Indeed, we find either negligible or significant substitution effects on both technology adoption and R&D environmental investment taken in first differences. This somehow confirms the preliminary evidence that emerged in the descriptive statistics concerning the evolution of our outcome variables. However, as aforementioned, our results could be affected by omitted variable bias because we may not account for all information that the public authorities use to fund eligible companies.

6 Conclusions

In this study, we examine the impact of a public environmental subsidy provision on the environmental investment, in a sample of 1,849 Dutch private companies in non-service industries, during the 2006-2009 period. Our policy evaluation aims to provide novel evidence on the effectiveness of public environmental subsidy in supporting the adoption of the existing abatement technologies and in indirectly stimulating green R&D investment in recipient firms. Specifically, our goal is to identify the heterogeneous effects associated with the provision of several amounts of subsidy (treatment doses), i.e., we attempt to determine in which cases policy makers should re-allocate the public resources devoted to the adoption of cleaner technologies, and, by means of this environmental subsidy, understand whether indirect effects that propel R&D efforts in green oriented activities exist. Furthermore, combining information from firm production and environmental costs surveys, we can effectively distinguish between the treatment effects on process-integrated and end-of-pipe environmental investment, and compare the indirect effects on the in-house green R&D with the effects on green R&D performed externally.

Our findings differ depending on whether the outcome variables are taken in levels or first differences. Regarding the analysis in levels, we find non-significant effects, except for firms receiving a subsidy of around 1,000 (7,400) EUR, an increase of 1,000 EUR may induce a reduction (increase) in their total environmental investment of 384 (242) EUR. However, in the analysis in first differences, it appers that firms substitute private environmental investment with public resources in the majority of cases. We find significant negative treatment effects for the group of medium-large subsidy (7,400-20,000 EUR) recipients: an increase of 1,000 EUR may decrease the difference between the current and past green investment in a range of 789-2,091 EUR. When separating the total environmental investment for technology adoption in its two components, it emerges that the crowding-out effects more likely occur for the process-integrated rather than for the end-of-pipe component. We primarily rely upon the results obtained from the analysis in first differences because it allows us to remove the unobserved two-year-invariant firm specific term that may potentially correlate with the observables and therefore bias our estimates.

Although no reliable evidence of any positive (i.e., additionality) effect of the public environmental subsidy is found, we further investigate whether an indirect effect on the green R&D investment exists. Focusing on results in first differences exclusively, we find that nearly negligible negative effects for the internal environmental R&D investment, but non-negligible substitution effects emerge for the complementary part. Specifically, a 1,000 EUR increase in the subsidy may induce a reduction in the difference between current and past external environmental R&D investment of 39-146 EUR for firms benefiting of 7,400-20,000 EUR.

Overall, our empirical analysis appears to suggest a substantial re-design of both the modulation and targeting of the environmental policy tool under evaluation. Although the potential limitation of our study is the exact identification of the assignment rule used by the policy makers, i.e., we may not observe all variables considered to determine the amount publicly provided, the absence of additionality effects for all treatment doses definitely appears worrisome.

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Table 1: Descriptive Statistics

Variable	*Mean*	*St.Dev.*
Treatment variable		
Environmental subsidy	22.554	120.604
ln environmental subsidy	1.026	1.639
Outcome variables in level		
Total environmental investment for adoption	180.056	1007.761
Process integrated environmental investment	70.449	583.462
End-of-pipe environmental investment	109.607	604.317
Total environmental R&D	53.186	384.283
Internal environmental R&D	41.596	338.283
External environmental R&D	11.589	58.955
Outcome variables in first differences		
Total environmental investment for adoption	-77.558	1389.167
Process integrated environmental investment	-55.826	1288.595
End-of-pipe environmental investment	-21.733	700.976
Total environmental R&D	-21.161	283.642
Internal environmental R&D	-17.270	256.307
External environmental R&D	-3.890	44.306
Pre-treatment variables		
ln capital stock	6.549	1.789
ln employment	4.337	1.135
Environmental investment intensity	0.782	3.156
R&D intensity	0.223	0.283
Export status	0.222	0.416
< 10 employees	0.045	0.208
$10 - 49$ employees	0.460	0.499
$50 - 99$ employees	0.201	0.401
$100 - 499$ employees	0.162	0.369
> 499 employees	0.131	0.337
Other subsidy type1	0.523	0.499
Other subsidy type2	0.041	0.199
Other subsidy type3	0.431	0.495
Observations	1,849	

Notes: Monetary values are reported in thousands of euros and deflated at 2000 year price level.

Table 2: Continuous Treatment Matching – The Effect of Environmental Subsidy on Total Environmental Investment for Adoption.

Treatment Dose		*Treatment Effect on Level*			*Treatment Effect on First Difference*		
Log-level	Level	Effect	St.dev.	T-stat	Effect	St.dev.	T-stat
0.000	1,000.000	-0.384	0.146	-2.622	-0.149	0.182	-0.820
0.500	1,648.721	-0.196	0.188	-1.044	-0.043	0.232	-0.185
1.000	2,718.282	0.022	0.202	0.109	-0.088	0.245	-0.358
1.500	4,481.689	0.135	0.137	0.992	-0.380	0.278	-1.369
2.000	7,389.056	0.242	0.097	2.495	-0.789	0.407	-1.941
2.500	12,182.490	0.305	0.365	0.837	-1.362	0.757	-1.800
3.000	20,085.540	0.130	0.792	0.165	-2.091	1.278	-1.636
3.500	33,115.450	0.175	1.324	-0.132	-3.032	2.005	-1.512
4.000	54,598.150	-0.208	1.941	-0.107	-4.064	2.785	-1.459

Note: Treatment effects refer to a dose increase of EUR 1,000. Monetary values are deflated at 2000 year price level.

Table 3: Continuous Treatment Matching – The Effect of Environmental Subsidy on Process Integrated Environmental Investment.

Treatment Dose		*Treatment Effect on Level*			*Treatment Effect on First Difference*		
Log-level	Level	Effect	St.dev.	T-stat	Effect	St.dev.	T-stat
0.000	1,000.000	-0.150	0.046	-3.276	-0.099	0.110	-0.897
0.500	1,648.721	-0.116	0.096	-1.217	-0.027	0.142	-0.180
1.000	2,718.282	-0.052	0.118	-0.435	-0.064	0.151	-0.422
1.500	4,481.689	-0.001	0.076	-0.012	-0.263	0.137	-1.920
2.000	7,389.056	0.090	0.045	2.017	-0.525	0.100	-5.240
2.500	12,182.490	0.192	0.197	0.975	-0.903	0.209	-4.328
3.000	20,085.540	0.257	0.401	0.642	-1.365	0.431	-3.170
3.500	33,115.450	0.297	0.680	0.437	-1.977	0.719	-2.751
4.000	54,598.150	0.472	1.005	0.470	-2.635	1.071	-2.460

Note: Treatment effects refer to a dose increase of EUR 1,000. Monetary values are deflated at 2000 year price level.

Table 4: Continuous Treatment Matching – The Effect of Environmental Subsidy on End-of-Pipe Environmental Investment.

Treatment Dose		*Treatment Effect on Level*			*Treatment Effect on First Difference*		
Log-level	Level	Effect	St.dev.	T-stat	Effect	St.dev.	T-stat
0.000	1,000.000	-0.234	0.044	-5.382	-0.051	0.154	-0.331
0.500	1,648.721	-0.080	0.128	-0.625	-0.014	0.062	-0.229
1.000	2,718.282	0.074	0.113	0.650	-0.021	0.102	-0.208
1.500	4,481.689	0.136	0.093	1.461	-0.116	0.105	-1.098
2.000	7,389.056	0.152	0.039	3.870	-0.265	0.093	-2.865
2.500	12,182.490	0.113	0.155	0.732	-0.465	0.206	-2.260
3.000	20,085.540	-0.127	0.323	-0.392	-0.739	0.524	-1.410
3.500	33,115.450	-0.472	0.568	-0.831	-1.078	0.986	-1.093
4.000	54,598.150	-0.680	0.848	-0.803	-1.462	1.393	-1.050

Note: Treatment effects refer to a dose increase of EUR 1,000. Monetary values are deflated at 2000 year price level.

Table 5: Continuous Treatment Matching – The Effect of Environmental Subsidy on Total Environmental R&D Investment.

Treatment Dose		*Treatment Effect on Level*			*Treatment Effect on First Difference*		
Log-level	Level	Effect	St.dev.	T-stat	Effect	St.dev.	T-stat
0.000	1,000.000	-0.018	0.006	-2.971	-0.009	0.018	-0.500
0.500	1,648.721	-0.028	0.011	-2.515	-0.007	0.025	-0.287
1.000	2,718.282	-0.009	0.016	-0.556	-0.011	0.029	-0.370
1.500	4,481.689	0.022	0.019	1.163	-0.032	0.028	-1.112
2.000	7,389.056	0.087	0.029	2.974	-0.065	0.022	-2.999
2.500	12,182.490	0.174	0.047	3.677	-0.110	0.021	-5.280
3.000	20,085.540	0.276	0.081	3.399	-0.168	0.035	-4.794
3.500	33,115.450	0.386	0.123	3.143	-0.238	0.058	-4.112
4.000	54,598.150	0.557	0.171	3.253	-0.323	0.096	-3.382

Note: Treatment effects refer to a dose increase of EUR 1,000. Monetary values are deflated at 2000 year price level.

Table 6: Continuous Treatment Matching – The Effect of Environmental Subsidy on Internal Environmental R&D Investment.

Treatment Dose		*Treatment Effect on Level*			*Treatment Effect on First Difference*		
Log-level	Level	Effect	St.dev.	T-stat	Effect	St.dev.	T-stat
0.000	1,000.000	0.008	0.011	0.688	-0.013	0.008	-1.579
0.500	1,648.721	0.008	0.010	0.828	-0.021	0.010	-2.067
1.000	2,718.282	0.019	0.006	3.015	-0.022	0.012	-1.940
1.500	4,481.689	0.027	0.008	3.341	-0.025	0.010	-2.546
2.000	7,389.056	0.046	0.009	4.891	-0.025	0.016	-1.555
2.500	12,182.490	0.069	0.017	4.049	-0.023	0.033	-0.712
3.000	20,085.540	0.091	0.028	3.276	-0.022	0.055	-0.390
3.500	33,115.450	0.112	0.043	2.610	-0.018	0.087	-0.200
4.000	54,598.150	0.155	0.060	2.602	-0.012	0.125	-0.094

Note: Treatment effects refer to a dose increase of EUR 1,000. Monetary values are deflated at 2000 year price level.

Table 7: Continuous Treatment Matching – The Effect of Environmental Subsidy on External Environmental R&D Investment.

Treatment Dose		*Treatment Effect on Level*			*Treatment Effect on First Difference*		
Log-level	Level	Effect	St.dev.	T-stat	Effect	St.dev.	T-stat
0.000	1,000.000	-0.026	0.006	-4.575	0.004	0.006	0.654
0.500	1,648.721	-0.037	0.008	-4.596	0.014	0.016	0.891
1.000	2,718.282	-0.028	0.009	-3.175	0.012	0.016	0.742
1.500	4,481.689	-0.005	0.006	-0.837	-0.007	0.007	-0.915
2.000	7,389.056	0.042	0.010	4.187	-0.039	0.018	-2.137
2.500	12,182.490	0.106	0.020	5.206	-0.086	0.049	-1.772
3.000	20,085.540	0.184	0.030	6.161	-0.146	0.088	-1.662
3.500	33,115.450	0.275	0.051	5.333	-0.221	0.139	-1.587
4.000	54,598.150	0.402	0.071	5.654	-0.311	0.201	-1.551

Note: Treatment effects refer to a dose increase of EUR 1,000. Monetary values are deflated at 2000 year price level.

Figure 1: Continuous Treatment Matching – The Effect of Environmental Subsidy on Total Environmental Investment for Adoption in Levels.

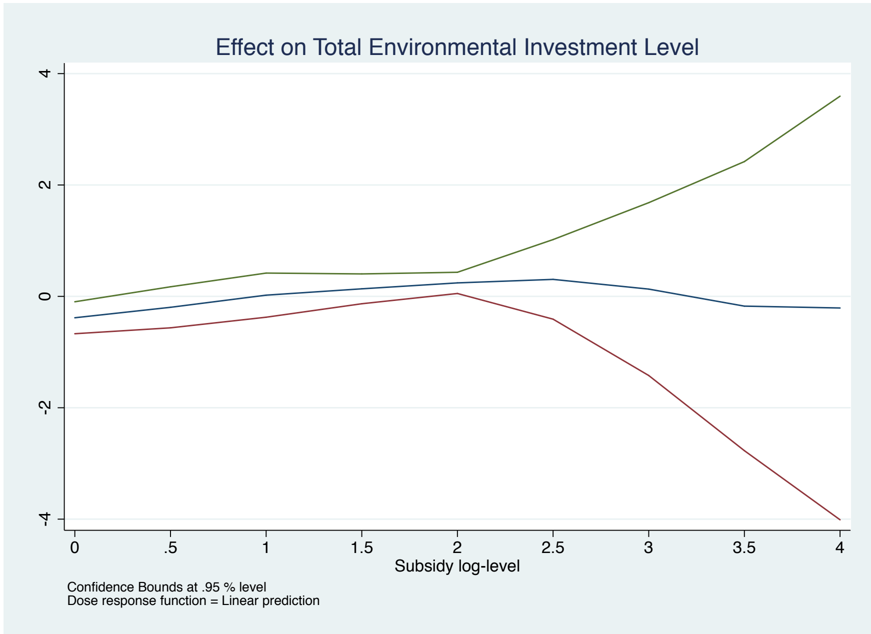

Figure 2: Continuous Treatment Matching – The Effect of Environmental Subsidy on Total Environmental Investment for Adoption in First Differences.

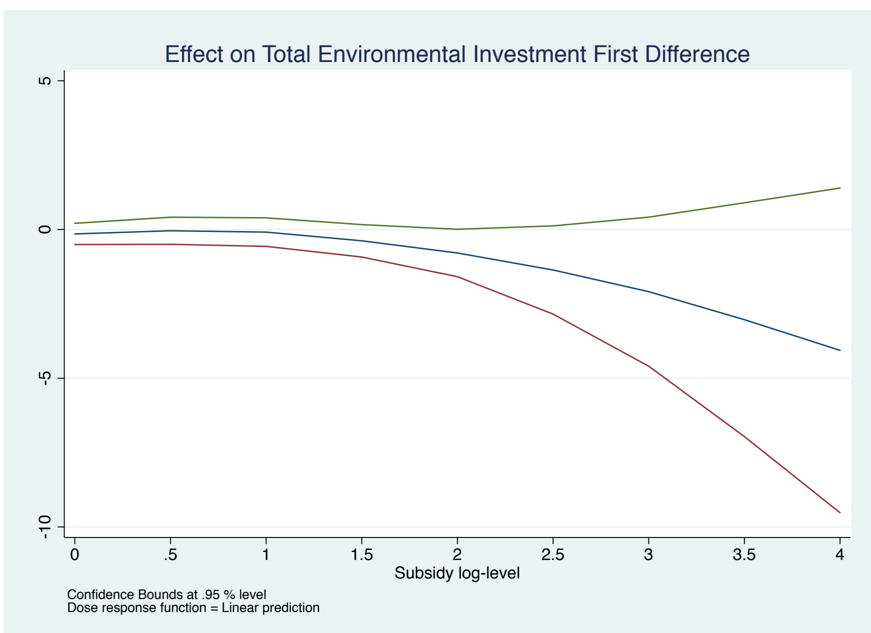

Figure 3: Continuous Treatment Matching – The Effect of Environmental Subsidy on Process Integrated Environmental Investment in Levels.

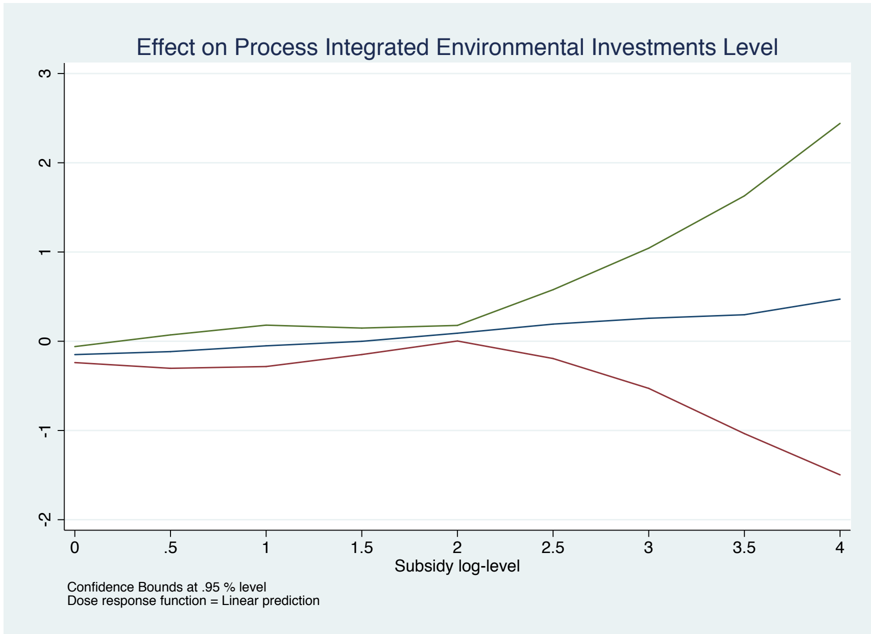

Figure 4: Continuous Treatment Matching – The Effect of Environmental Subsidy on Process Integrated Environmental Investment in First Differences.

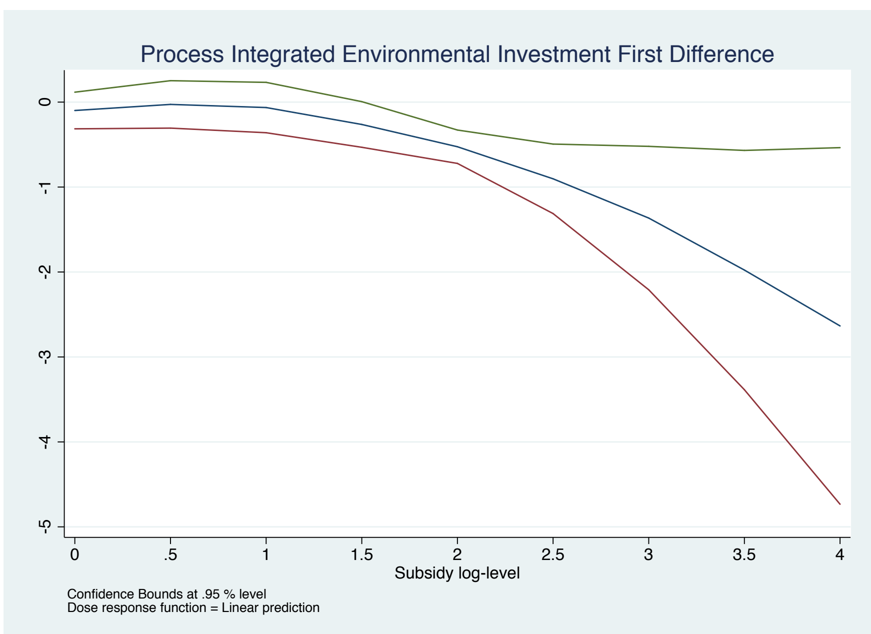

Figure 5: Continuous Treatment Matching – The Effect of Environmental Subsidy on End-of-Pipe Environmental Investment in Levels.

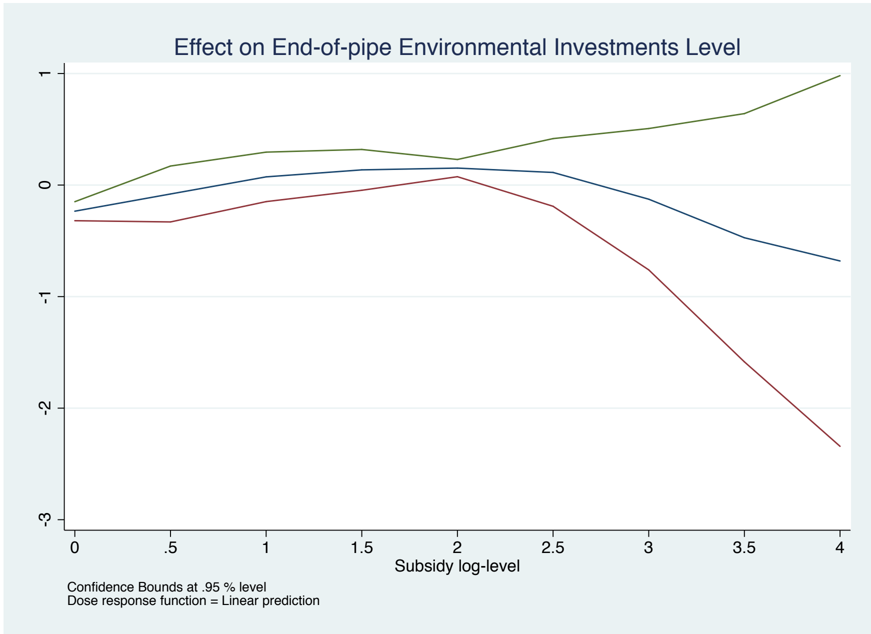

Figure 6: Continuous Treatment Matching – The Effect of Environmental Subsidy on End-of-Pipe Environmental Investment in First Differences.

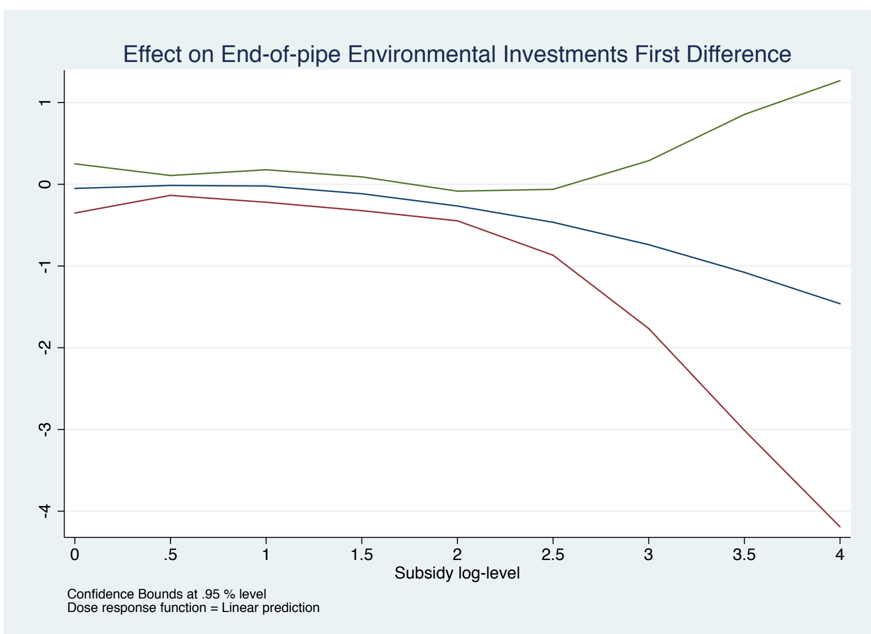

Figure 7: Continuous Treatment Matching – The Effect of Environmental Subsidy on Total Environmental R&D in Levels.

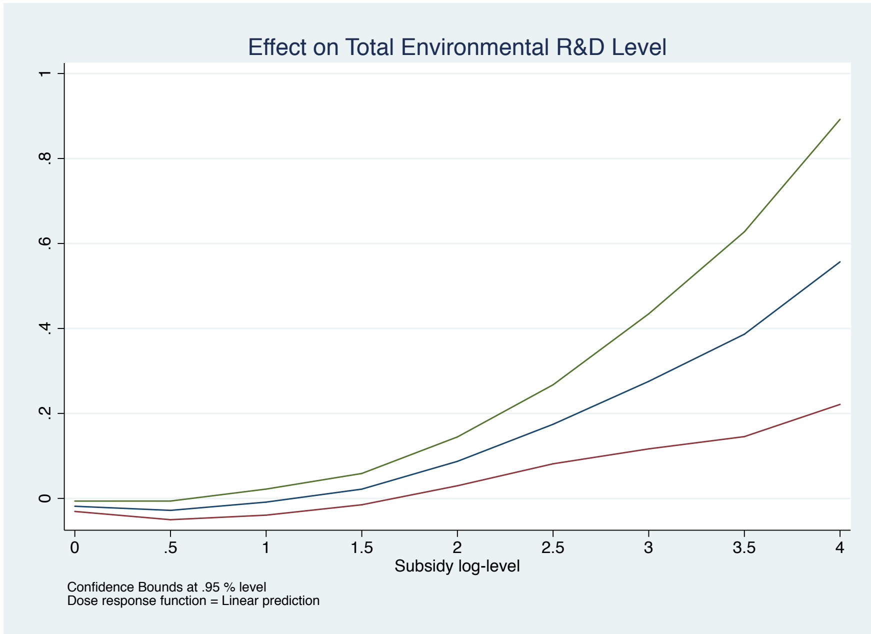

Figure 8: Continuous Treatment Matching – The Effect of Environmental Subsidy on Total Environmental R&D in First Differences.

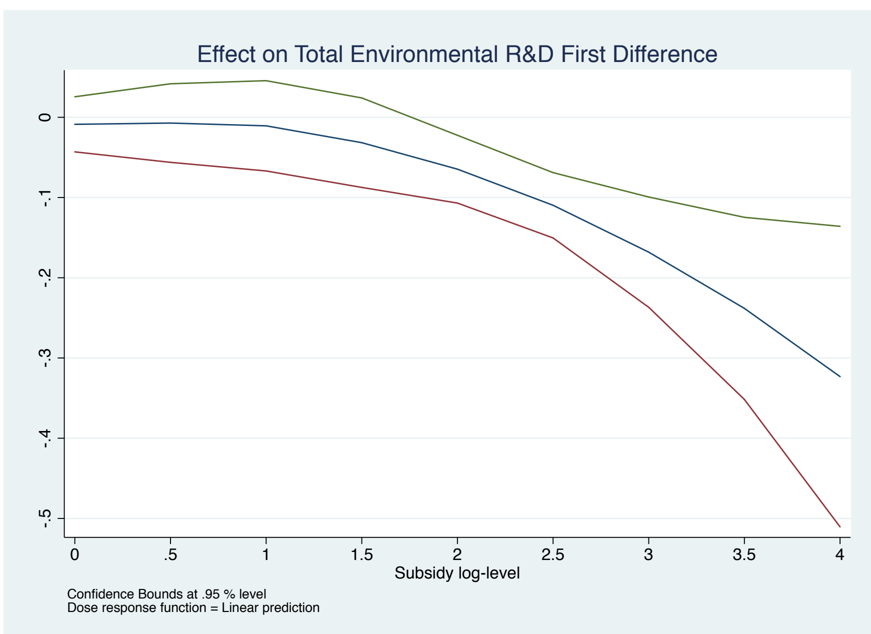

Figure 9: Continuous Treatment Matching – The Effect of Environmental Subsidy on Internal Environmental R&D in Levels.

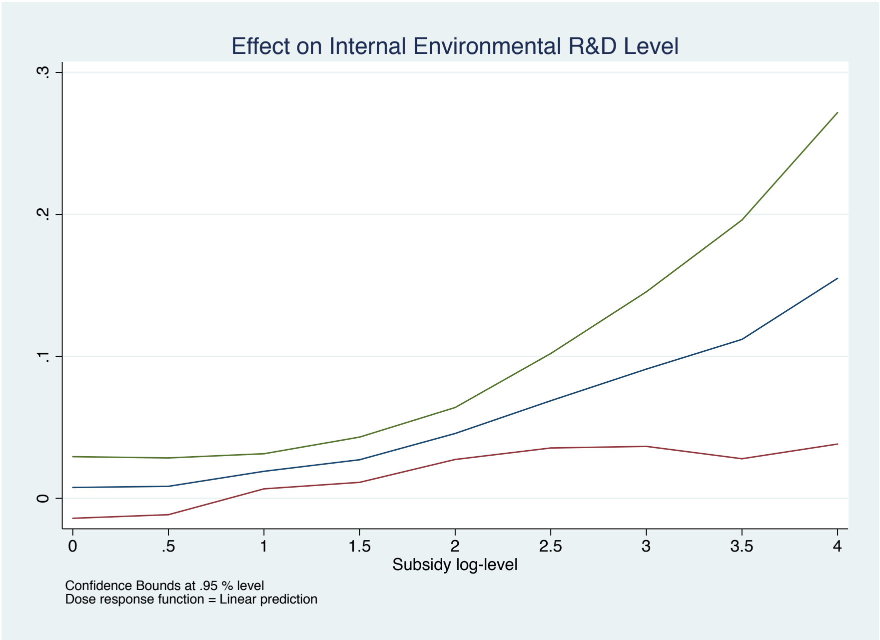

Figure 10: Continuous Treatment Matching – The Effect of Environmental Subsidy on Internal Environmental R&D in First Differences.

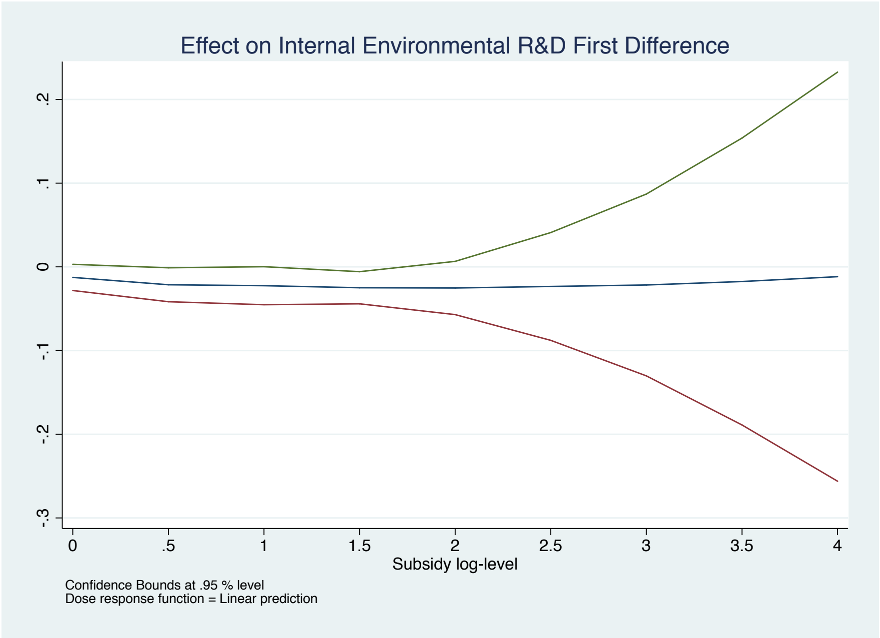

Figure 11: Continuous Treatment Matching – The Effect of Environmental Subsidy on External Environmental R&D in Levels.

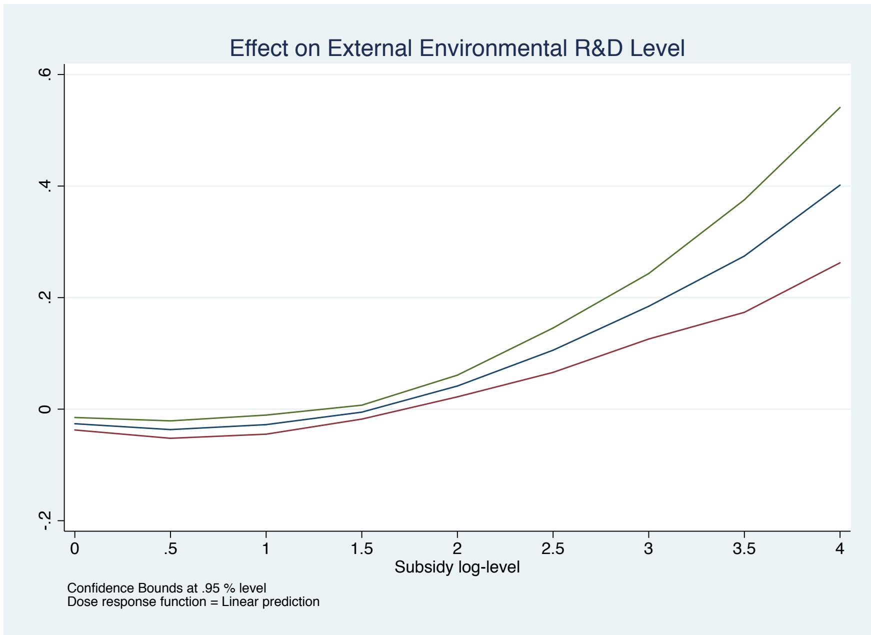

Figure 12: Continuous Treatment Matching – The Effect of Environmental Subsidy on External Environmental R&D in First Differences.