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Abstract

Significant policy effort is devoted to stimulate the development, adoption and diffusion of environmentally-friendly technology. Sceptics worry about the effects of regulation-induced environmental technology on firms' competitiveness. Since innovation is a crucial productivity driver, a potential crowding out of inventive efforts could increase the cost of mitigating environmental damage. Using matching techniques, we study the short-term effects of regulation-induced environmental technology on non-green innovative activities for a sample of firms in Germany. We find indeed some evidence for a crowding out of the firms' in-house R&D. The estimated treatment effect is larger for firms that are likely to face financing constraints. However, we do not find negative effects on the number of ongoing R&D projects, investments in innovation-related fixed assets or on the outcome of innovation projects. Likewise, for firms with subsidy-backed environmental innovations no crowding out is found.

Keywords — Environmental Policy, Regulation, R&D, Technological Change, Innovation, Crowding Out

JEL Codes — O32, O33, Q55

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1 Introduction

Rising environmental concerns, in particular on climate change, have triggered numerous policy initiatives aimed at limiting further damage. To achieve this objective the invention and implementation of cleaner production technologies is vital (Goulder and Schneider 1999, Goulder and Mathai 2000, Gerlagh 2008). Environmental innovation, however, creates externalities that may require policy action to provide sufficient incentives for research and development (R&D) directed at exploring new technologies as well as for the adoption of greener production methods.

Although environmental policies may be crucial to avoid the socio-economic cost of environmental disasters, economic policy is also concerned not to threaten competitiveness of the business sector. Innovation has long been understood to be an essential driver of such competitiveness (Solow 1957, Griliches 1979, Griliches and Mairesse 1984). Thus, in principle any environmental policy should be designed such that it avoids a crowding out of other inventive efforts in the affected firms. In other words, the role of opportunity cost of environmental regulation ought to be taken into account as "[...] any new environmental R&D that comes at the expense of other R&D investment will dampen the cost-savings potential of induced technological change" (Popp and Newell 2012, p. 980).

Environmental regulation, especially command-and-control regulation, has been particularly suspect to being a source of crowding out effects. Regulated firms are often obliged to devote substantial financial and human resources to fulfilling the given requirements. The resources allocated to compliance efforts may then simply lack for other innovation projects and firms may be forced to scale down their innovative activities at least in the short-term. The review of the existing literature shows that only little empirical work has tried to assess the existence or even the magnitude of a potential crowding out of policy-induced technological change. With few exceptions such as Roediger-Schluga (2003) and Popp and Newell (2012), firm-level analyzes on this issue are basically non-existent.

This study therefore aims to contribute to the understanding of potential side-effects of environmental regulation at the firm-level. In particular, we study the effects of regulation-induced environmental technology adoption on the firms' other innovative activities. A crowding out is thus understood as a displacement of productive inventive efforts by regulation-induced spending for pollution control technology, regardless whether this is due to own (environmental) R&D or the acquisition of abatement technology. We employ econometric treatment effects models as well as instrumental variable regressions for estimating the treatment effect on the treated. A treatment in our case means that regulation had induced these firms to develop, adopt or implement environmental-friendly technologies. Firm-level survey data covering the period 2006 to 2008 allows us to assess whether environmental policy has been effective for the individual firm.

What is more, environmental policy programs often include public R&D support, for instance, via direct subsidies (Newell 2007, de Coninck, Fischer, Newell and Ueno 2008). In the following study, we therefore consider subsidies that triggered environmental technology implementation as an (additional) treatment. In the context of this paper, inducing increased efforts on environmental R&D via subsidies may come at the cost of other innovative efforts if public as well as private R&D funding is diverted away from other areas. On the other hand, it can be argued that subsidies may be needed to prevent a potential crowding out, especially in firms with constrained access to financial resources.

This study further adds to previous research as we draw from representative data covering small and medium-sized firms as well as large firms in Germany active in a broad range of industries. Germany provides an ideal testing ground for our analysis as it has been rather active in implementing environmental regulation and subsidy schemes to stimulate environmental technology.

The article proceeds as follows. The next section provides a brief overview of related literature and German laws and regulations relevant for our study. Section 3 sets out our empirical strategy. Section 4 describes the data from the German Community Innovation Survey (CIS) used for the empirical analysis. Results will be presented in section 5 before section 7 concludes.

2 Previous Research and Contribution

Given the market failures associated with environmental innovations[1], many governments in industrialized economies attempt to correct them by using policy instruments. Besides empirical evidence for price-induced environmental innovation[2], the efficacy of policy for inducing green technological change has been stressed: "In general, policy, rather than prices, appears to be the main driver of innovation in these technologies" (Johnstone, Haščič and Popp 2010, p.146).

A detailed overview of the existing policy tools and their potential effects on firm-level activities is beyond the scope of this article[3] as our focus is on whether policy-induced environmental technology invention and adoption come at the cost of other inventive efforts.

A crowding out may question the premise of cost-free controls and may lead to competitiveness losses at the firm, industry and national level. Despite the policy relevance of these considerations, only very limited empirical evidence exists, especially at the firm-level. Although, for instance, Lanjouw and Mody (1996) who study patent applications find that environmental regulation stimulates related innovations, they cannot rule out that there had been a crowding out, i.e. that regulated firms had been even more innovative in the absence of regulation.

As one of the first empirical contributions, Gray and Shadbegian (1998) study directly a crowding out effect of pollution control spending on conventional (i.e. other) investments in the pulp and paper sector. They find that a Dollar spent for abatement investments reduces any other productive investment spending by 1.88 Dollars. Roediger-Schluga (2003) uses firm-level survey data to descriptively study how Austrian Volatile Organic Compound (VOC) emission standards affect competitiveness in a small sample of selected Austrian manufacturers and whether compliance-stimulated innovation crowded out other, more productive R&D. He

[1] "Pollution creates a negative externality, and so the invisible hand allows too much of it. Technology creates positive externalities, and so the invisible hand produces too little of it" (Popp, Newell and Jaffe 2009, p.3).

[2] For instance Newell, Jaffe and Stavins (1999) find that increasing energy prices are associated with new energy-saving technology for air conditioners and Popp (2002) observes patent applications for energy-saving technologies to respond to increasing energy prices.

[3] See Jaffe, Newell and Stavins (2002) for a review of the literature. Rennings and Rexhäuser (2011) provide an overview of policies in place in Germany since the 1960s.

finds neither unequivocally negative nor positive effects on competitiveness of manufacturers of regulated products. He concludes that some "firms devoted almost their entire R&D budget to developing compliant products" which suggests that - at least to some extent - compliance efforts may have displaced or postponed other R&D projects.

Popp and Newell (2012) is another notable exception studying whether new energy R&D crowds out other types of R&D spending. First, they study the effect of economy-wide increases in energy R&D on total R&D spending at the industry level and find little evidence of a crowding out across sectors. Secondly, at the firm level, they use patent data to examine changes in the research portfolios of companies engaged in alternative energy R&D and find that green patenting does crowd out other types of patenting. Yet, their results also suggest a high social value of the former as alternative energy patents are cited more frequently. Since the sample of firms in Popp and Newell (2012) consists of large, publicly traded and patent-active firms, no conclusions can be drawn for small and medium-sized firms, which are more likely to be affected by financing constraints for R&D[4]. Especially in financially constrained firms the amount of resources allocated to environmental technology reduces those resources available for other innovation projects. If firms additionally have to re-allocate financial resources to compliance efforts due to regulations and standards, research budgets, especially of long-term research projects in non-environmental-related areas, may be scaled-down. Thus, although environmental technologies are socially very valuable, a crowding out of other fundamental R&D may dampen the social benefits to environmental regulation. When implementing environmental regulation that aims at stimulating environmental technology at the firm-level, it seems crucial to think about sources of funding for such activities, for instance, via subsidy schemes. Fischer and Newell (2004) compare R&D subsidies and other policies aimed at reducing carbon emissions in the U.S. electricity sector. They conclude, however, that R&D subsidies are the least effective policy tool for reducing emissions. Yet, they do not consider social returns from knowledge spillovers that justify R&D subsidies and do not take

[4]See for instance Czarnitzki and Hottenrott (2011) for recent empirical evidence for Germany. They show that financial constraints for R&D decrease monotonically with firm size, while this is not the case for investments in physical assets for which financial constraints are less binding.

into account the use of a policy mix in which subsidies are only part of the policy spectrum.

Few other studies focus on the industry or national level. Jaffe and Palmer (1997) find ambiguous evidence for regulation-induced innovation at the industry level. More precisely, they find pollution abatement costs expenditure (PACE) as a proxy of regulatory stringency to have no significant impact on patent applications, indicating a re-direction rather than a crowding out of patents as a measure for innovation output. On the other hand, they find a positive impact of PACE on firms' R&D expenditures controlling for industry specific effects. Similarly, Brunnermeier and Cohen (2003) find PACE to have a significant positive impact on firms' overall patent applications.

The main reason for little empirical evidence at the firm-level may be related to measurement problems due to a lack of sufficiently disaggregated data and the difficulties in distinguishing regulation-induced and other innovative activities. The survey-based data set used for the following analysis has several features that address these issues. The major advantage is that we can identify firms that - as a reaction to the policy in place - implemented some sort of environmental technology. Such technologies comprise, for instance, ways to reduce energy and material consumption as well as waste, improved recycling methods and measures to limit air, soil and water pollution. In other words, rather than using a proxy for the stringency of environmental regulation we derive indicators from a survey that allow us to identify directly whether regulation had indeed induced environment-friendly technological changes in a particular firm. This does, but not exclusively, cover cases in which firms developed the new technology themselves in addition to firms that implemented environmental technology developed by others. Taking that aspect into account is crucial as the diffusion of environmental technology strongly depends on the adoption of existing technologies. Although it can be argued that the former case of technology development is more resource intensive and hence more likely to crowd-out other R&D, it should also be considered that the implementation of these technologies in other firms may require critical amounts of human and financial resources. Such technologies not only need to be acquired, but they also have to be incorporated into production processes, potentially requiring adjustment to and alignment with already implemented technologies. Moreover, new technologies usually require training of employees. Our approach that takes the costs related to environmental innovation at the firm level into account accommodates for the fact that compliance costs (which define the impact of the environmental regulation) are highly firm-specific.

2.1 Regulation and Environmental Innovation

There is a considerable body of theoretical research on the impact of regulation on environmental innovation that studies the effects of different regulatory instruments like tradable permits, taxes or standards on the R&D incentives for pollution control technologies[5]. Much less work exists regarding the impact on both pollution control and productive innovation investments. Magat (1978) assumes a profit-maximizing firm subject to pollution control regulation that has to allocate a fixed R&D budget over productive and abatement technologies which are substitutes. He concludes that a constant pollution tax provides decreasing incentives for abatement R&D spending over time and therefore provides more incentives for investment into productive R&D. Roughly speaking, this is because productive R&D's returns increase more rapidly than those of abatement spending if the tax is constant over time. Conversely, a fixed emission standard has the feature that an affected firm can grow only if it further invests in abatement R&D at the expense of investment in productive R&D. Put it otherwise, R&D spent on pollution control crowds out conventional R&D in case of an emission standard. This effect is smaller and decreases over time for a fixed pollution tax rate (or a cap and trade system with a constant cap)[6]. Thus, the extent to which a crowding out occurs may depend crucially on the policy design.

The number of regulations in force in Germany has increased substantially during the past decades (see Figure 1). An overwhelming part of these laws and directives are command-and-control regulations (see Frondel, Horbach and Rennings 2007). This is strongly mirrored in the firm survey used for the present

[5] Popp et al. (2009) and review much of this literature.

[6] Please note that the results of Magat (1978) crucially depend on the degree of labor substitutability. If substitutability was very easy, an emission standard leads to a relative increase in conventional R&D over time.

analysis.[7]

The majority (95.76 percent) out of 377 usable responses reported command-and-control regulations as reasons for technology adoption between 2006 until 2008 (see Table A.2). The most frequently mentioned law is the German equivalent to the 1970 US Clean Air Act, the so called Federal Pollution Control Act (Bundes-Immissionsschutzgesetz) which came into force in 1974 and is the most important German regulation to restrict air pollution. Together with its administrative provision, the "TA Luft" (Technical Instructions on Air Quality Control) that sets emission limits, the German Federal Pollution Control Act accounts for about 23.87 percent of the responses in our survey. In principle, one would not have expected such rather ancient regulations to provide any incentives for technological change today after compliance had been achieved in the past. However, most of these regulations such as the Federal Pollution Control Act have a dynamic character that requires firms to operate the current state of the art abatement technology. Also of high importance were two relatively new regulations that restrict the use of hazardous chemicals. The RoHS directive ("Restriction of Hazardous Substances" enforced in 2006) of the European Community restricts the use of lead, cadmium, mercury, and some other metals in electronic devices and initiated process innovations in 14.85 percent of the firms in our sample. Moreover, 11.41 percent of the firms report the REACH directive, which stands for "Registration, Evaluation, Authorization and Restriction of Chemicals", that came into force in 2007 was the reason for technological adaption of their production processes.

Another 8.48 percent mentioned the Energy Saving Regulation (EnEV) from 2002 which had been revised in 2007. It sets energy efficiency requirements for buildings, especially for new ones. In general, more than 40 different command-and-control regulations were named by firms as drivers of technology adoption. Almost all of them were revised or augmented in the sample period 2006-2008, or shortly before.

Only in about 1.86 percent of all responses, firms stated market-based regula-

[7] Unfortunately, only a fraction of the firms that adopted pollution control technology responded to the survey question of what specific regulation(s) or law(s) required adoption of abatement technology. These answers, nevertheless, provide an indication of those regulations that initiated the green innovations in the firms that we study in detail in the following.

tions or energy taxes as the reasons for technological change[8]. The cited market based regulation is the European Emission Trading Scheme (EU ETS) for greenhouse gases that came into force in 2005. To add further evidence, we linked our firm database to the Community Independent Transaction Log (CITL) that reports every single firm that is covered in the EU ETS. In our data, only 1.22 percent of the firms were identified to be subject to this cap and trade system. This confirms that firms in our sample are mainly affected by command-and-control regulations. Based on theoretical consideration by Magat (1978) and in light of the predominance of the command-and-control character of these regulations, we could therefore expect that in our setting a (partial) crowding out of other R&D may indeed be more likely by compliance spending compared to a setting in which market-based policy instruments are prevailing.

3 Identification Strategy

In the following, we are interested in the effects of regulation-induced environmental innovation on the firms' conventional innovative efforts. In this setting, we therefore consider the introduction of an environmentally-friendly innovation due to regulation to be the observed "treatment".[9] Our main research question can be illustrated by an equation describing the average treatment effect on the treated firms

$$E(\alpha_{TT}) = E(Y^T|R=1) - E(Y^C|R=1) \tag{1}$$

where Y^T is an outcome variable[10] and the status R indicates the group: $R = 1$ is the treatment group and $R = 0$ the non-treated firms whereby the treatment refers to regulation-induced environmental technology adoption as identified from the firms' self-reported information in the survey. Y^C is the potential outcome which would have been realized if the treatment group ($R = 1$) had not been treated. While $E(Y^T|R = 1)$ is directly observable, this is not the case for $E(Y^C|R = 1)$. However, as the probability to be subject to effective regulation is not random

[8]The remaining percentages account for the ISO 14001 standard or other voluntary agreements mentioned as reason for innovation.

[9]See subsection 4.1 for more details on the definition of the treatment indicators.

[10]See subsection 4.2 for details on the outcome variables.

$(E(Y^C|R=1) \neq E(Y^C|R=0))$ a potential "selection bias" may arise so that the counterfactual situation cannot simply be approximated by the average outcome of the non-regulated firms.[11] The same applies to the receipt of a subsidy. Thus, we have to take into account that not all firms are affected by regulation and not all firms received a subsidy that supported their environmental technology. Investigating the behavior of firms that responded to regulation therefore requires to take this selection into account. The conditional independence assumption (CIA) $Y^C \perp R|X = x$ has been introduced by Rubin (1977) to overcome this selection problem. That is in our case, regulation-induced environmental technology adoption and the outcome variable of interest like non-green R&D spending are statistically independent for firms with the same set of exogenous characteristics X. The result of the matching approach is such that the potential "untreated outcome" of treated firms is constructed from a control group of firms that did not react to environmental regulation by introducing some form of environmental technology. Hence, the matching allows to compare the outcome of treated firms to the hypothetical outcome of these firms if they had not been treated. Differences in the outcome variable between these "groups" are then attributed to the treatment. Consequently, if the CIA holds, it follows that

$$E(Y^C|R=1,X) = E(Y^C|R=0,X). \tag{2}$$

Thus, the average treatment effect on the treated can be written as:

$$E(\alpha_{TT}) = E(Y^T|R=1,X=x) - E(Y^C|R=0,X=x) \tag{3}$$

In the following analysis, we employ several matching techniques that have the advantage not to require assumptions about functional forms and error term distributions.[12] Additionally, and in order to test the robustness of the results to a possible violation of the conditional independence assumption, we estimate instrumental variables models in which we account for endogeneity in the relationship

[11] For surveys of econometric techniques addressing selection bias see Heckman, Lalonde and Smith (1999) or Imbens and Wooldridge (2009).

[12] For discussions and applications of matching estimators see e.g. Angrist (1998), Heckman, Ichimura and Todd (1997) and Heckman, Ichimura, Smith and Todd (1998), Dehejia and Wahba (1999), and Smith and Todd (2005).

between the outcome variable and the treatment.[13]

First and as a benchmark, we perform a nearest neighbor (NN) propensity score matching. For that purpose, we pair each firm that had implemented a regulation-induced environmental technology with the single closest non-regulation-affected firm. Thus, for each treated firm we search for twins in the "potential control group" that share the same characteristics X as the treated firms. The pairs are defined based on the similarity in the estimated probability of having introduced a compliance technology based on regulatory pressure.

In other words, as matching criterion we use the propensity score stemming from a binary (probit) estimation using a dummy variable indicating the policy induction. Matching on the propensity score has the advantage not to run into the "curse of dimensionality" since we use only one single index as matching argument (Rosenbaum and Rubin 1983). Thus, the first step of our analysis is the specification and estimation of a probit model to obtain the propensity score $\hat{P}(X)$. Thereby it is essential to have enough overlap between the control and the treated group (common support) which means that in practice, the sub-samples of treated firms and firms in the control group are restricted to those with common support. Thus, in a second step we restrict the sample to common support. Therefore, we calculate the minimum and the maximum of the propensity scores of the potential control group and delete observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. Next, we pick one observation from the sub-sample of treated firms and remove it from the pool of treated firms. Then we calculate the Mahalanobis Distance (MD) between this firm and all non-treated firms in order to find the most similar control observation:

$$MD_{i,j} = (Z_j - Z_i)'\Omega^{-1}(Z_j - Z_i) \tag{4}$$

where Ω is the empirical covariance matrix of the matching arguments (Z) based on the sample of potential controls. After that, we select the observation with the minimum distance from the remaining control group. Unlike for the treated firms, we do not remove the selected control firms from the pool of potential controls. This routine is applied to all treated firms. Finally, the average effect on the treated

[13] See section A in the Appendix for the details.

can be calculated as the mean difference in the outcome variable(s) of the matched samples using the matched group as comparison.

$$\hat{\alpha}_{TT} = \frac{1}{n^T}\Big(\sum_i Y_i^T - \sum_i \hat{Y_i^C}\Big) \tag{5}$$

with $\hat{Y_i^C}$ being the counterfactual for i and n^T is the sample size of treated firms. We conduct t-tests on difference in means in the outcome variable(s) after the matching. A significant difference in means may then be attributed to the treatment. In our case, a smaller mean of the outcome variable, like non-environmental R&D in the group of regulated firms, would indicate a crowding out due to the regulation-induced environmental innovation.[14]

In order to assess the sensitivity of the results to the choice of the matching estimator, we perform serval other matching approaches. In particular, in addition to a two-nearest-neighbor matching, we want to reduce the risk of bad matches that may occur if the closest neighbor is far away. This can be avoided by imposing a caliper that limits the maximum propensity score distance. Finally, we perform Kernel matching (KM) that use weighted averages of all firms in the control group to construct the counterfactual outcome.[15] The major advantage of this approach is that more information is used and a lower variance can be achieved (Heckman et al. 1997, Heckman et al. 1998).

4 Data

The main data used for our analysis stem from the 2009 wave of the Mannheim Innovation Panel (MIP) that provides information for the years 2006-2008. The MIP is the German part of the European-wide Community Innovation Surveys (CIS). The survey is conducted annually by the Centre for European Economic Research (ZEW), the infas (Institut für angewandte Sozialwissenschaft) and the ISI Fraunhofer Institute on behalf of the German Federal Ministry of Education

[14]It should be noted that, since we perform sampling with replacement to estimate the counterfactual situation, an ordinary t-statistic on mean differences is biased as it does not take the possibility of repeated observations into account. We therefore follow Lechner (2001) and calculate an asymptotic approximation of the standard errors that corrects for this bias.

[15]See Smith and Todd (2005) for technical details.

and Research. The target population covers all firms with at least 5 employees in the German business sector.[16] Besides information on innovative activities and general characteristics of the firms, the 2009 wave of the survey collected detailed information on the adoption and production of environmental technologies. From this core data set, we are able to identify firms that adopted or implemented some form of environmental technology. This data has been complemented with a telephone survey that addressed this sub-sample of firms that indicated in the CIS that they had introduced environmentally-beneficial technologies. This additional telephone survey allowed to collect more detailed information on the respective environmental technologies. The most important information drawn from this data relates to the cost of introducing and implementing the environmental technology. We complement the survey data with information on the firms patent applications at the European Patent Office (EPO) and market concentration data from the German Monopoly Commission. Finally, we obtain a credit rating index for each firm from CREDITREFORM, Germany's largest credit rating agency.[17] After correction for outliers and elimination of incomplete records the final sample contains 2,521 firm-level observations.

4.1 The Treatment

Firms were asked if they had introduced some form of technology or production process with beneficial effects for the environment and if so, to indicate the initiation factors for the development and/or adoption and implementation of the technology. In particular, firms were asked to indicate if this innovation was driven by regulation, expectations about future regulation, public subsidies or, alternatively, by customer demand and/or by voluntary agreements at the sector level. We consider a firm to be treated if it introduced an environmentally-friendly technological innovation due to regulation (REG), but not due to customer demand for greener technologies or voluntary agreements. Moreover, the treatment variable thus takes the value one only, if regulations had induced the innovation, but the

[16] A detailed description of the survey data and the sampling method can be found in the background reports available at ZEW.

[17] See Czarnitzki, Hottenrott and Thorwarth (2011) for a more detailed description of the construction of this index.

firm did not receive subsidies for green technology of any type. Finally, we define a treatment variable SUB that takes the value of one if the receipt of a subsidy induced the introduction of environment-friendly technology.[18] Table 1 presents descriptive statistics for these treatment variables. It should be noted that the two treatments exclude each other, i.e. there is no overlap between the groups. For each of these treatments, we will estimate the treatment effect on the outcome variables. The control group consists of 2,177 firms that fall in neither of the two treatment categories. The ratio of treated to non-treated firms is favorable for a matching approach for both treatment indicators as the potential control group is sufficiently large.

Table 1: Summary Statistics of treatment indicators (2,521 obs.)

Variable	# Treated firms	Mean	Std. Dev.	Min	Max
REG	179	0.071	0.257	0	1
SUB	165	0.065	0.247	0	1

4.2 Outcome Variables

Based on information from the CIS and the complementary survey, we derive a handful of outcome variables on which a crowding out due to policy-induced environmental innovation might be suspected. The first one is the total number of innovation projects in the period 2006-2008 ($PROJECTS$). A firm that has to devote a substantial effort to fulfilling regulatory requirements may scale down their overall innovation activity by reducing the number of projects that are ongoing at the same time as the "environmental project". Secondly, we are interested in a further potential input crowding out reflected in total innovation-related spending ($INNO\_TOTAL$) which includes internal R&D ($INNO\_R\&D$), external R&D as well as innovation-related investment in physical capital ($INNO\_INV$). Such investments are usually considered to provide important assets complementary to the intangible knowledge created by R&D. A crowding out of internal R&D spending by regulation-induced innovation may have a substantial direct effect on

[18]Note that we test the robustness of our results to an alternative definition for which we consider a firm to be treated only if it was both regulation-affected and subsidy-affected in section 6.

innovation output and a long-term impact on the firms' overall performance. However, it can easily be argued that these general numbers of innovation spending do not account for the fact that regulation-induced innovation may have caused costs that the firms counted as innovation-related spending. In that case, we would underestimate a potential crowding out when looking at innovation spending as an outcome variable. To take account of this fact, we use information obtained through the additional telephone survey on the sub-sample of firms that indicated in the CIS that they had introduced an environmental innovation. These firms were asked to indicate the expenses related to the introduction of the environmental innovation. Thus, we can deduct this amount from the total innovation spending ($INNO\_TOTAL$) and obtain the net innovation spending for innovation ($INNO\_NET$) corrected for the regulation-induced investment.[19] This second survey addressed all firms in our sample that indicated that they had introduced some form of environmental innovation. On average, these firms stated they spend about 401 thousand euros (per year) on their environmental innovation. The median, however, is much lower with about 50 thousand euros. Moreover, we derive two measures for innovation outcomes. The first captures whether the firm had successfully introduced a product innovation to the market ($PRODUCT\_INNO$) and the second if market introductions were planned in the two years 2009 and 2010 following the survey ($PRODUCT\_LEAD$). Another measure accounts for the possibility of unsuccessful projects outcomes, i.e. it takes the value of one if the firm indicated that it had abandoned a innovation project after it had already started ($FAIL\_INNO$). We argued before that firms may rather scale down investment in areas that are not directly related to current production, but are rather long-term oriented and less certain in terms of returns like R&D. For reasons of comparison we therefore also include the firms'

[19]Since we can not disentangle the expenses for the environmental innovation by its R&D and fixed investment component, we calculate the net spending for the total innovation expenses only. However, it should be kept in mind that $INNO\_NET$ is only a rough approximation due to two limitations of the measure for environmental innovation expenses. First, these are total expenses which may have occurred over more than one year. Deducting them from $INNO\_TOTAL$ implicitly assumes that the expenses had all been made in one year. Secondly, not all firms may have included such expenses in the $INNO\_TOTAL$ as indicated in the CIS survey. For these firms, we may "correct" the innovation expenses wrongly and hence underestimate their true innovation expenditure. Nevertheless, as we can argue that the true total net innovation expenditure is somewhere between $INNO\_TOTAL$ and $INNO\_NET$ on average, we still want to include both of these variables in the set of outcome variables.

investment in non-innovation related assets (INV) as an outcome variable. Table 2 presents summary statistics for the outcome variables. Firms have more than seven ongoing innovation projects on average. The median number, however, is much smaller with only one current project per firm. In-house R&D is about 367 thousand euros on average and innovation-specific physical investment about 358 thousand euros. Total innovation expenditure amounts to about 908 thousand euros and total innovation expenditure net of all costs due to the environmental technology development or adoption is 744 thousand euros, on average. Non-innovation investment amounts to 2.5 million, on average. Forty-five percent of the firms had some form of product innovation during the survey period and 43.6 percent had product innovations in the pipe-line. Five percent of the firms had abandoned innovation projects.

Table 2: Summary Statistics of Outcome Variables (2,521 obs.)

Variable	unit	Mean	Std. Dev.	Min	Max
$PROJECTS$	#	7.893	42.795	0	1,500
$INNO\_TOTAL$	T€	908.241	3,478.525	0	30,000
$INNO\_R\&D$	T€	367.292	1,693.363	0	14,000
$INNO\_INV$	T€	357.946	1,395.983	0	12,000
$INNO\_NET$	T€	744.433	3,120.815	0	30,000
INV	T€	2,520.974	9,908.471	0	100,000
$PRODUCT\_INNO$	dummy	0.450	0.498	0	1
$PRODUCT\_LEAD$	dummy	0.436	0.496	0	1
$FAIL\_INNO$	dummy	0.050	0.216	0	1

4.3 Control Variables

A set of control variables is defined for inclusion in the first-stage probit model in which we model the selection into the treatment. Thus, these control variables are likely to impact the fact of whether or not a firm has introduced an environmental technology due to regulation and whether the firms used a subsidy to (co-)finance the introduction, respectively. In particular, we include the firms' logged value of fixed assets as more capital-intensive (as measured by the ratio of fixed assets to sales) firms may be more likely to be subject to environmental regulation ($logCAP$). Likewise, we control for firm size by including the logged number of employees ($logLAB$). Furthermore, we include the logged value of the firms' expenses on material and energy used in the production process ($logMAT$) as more material and energy-intensive firms may have higher incentives to introduce innovations that reduce consumption in these input factors and they may be more likely to be affected by regulation. The (logged) age of the firms is included ($logAGE$) to account for the fact that older firms may be more likely to have to renew part of their production capital which may make them more likely to make their production more environmentally-friendly when replacing their superannuated assets. The firms' labor productivity ($LABPRO$) measured as sales per employee is included to account for the firms' overall relative productivity. The firms' competitive environment is accounted for by including the Hirschman-Herfindahl measure of sales concentration (HHI). We further include a dummy to control for whether the firm is continuously R&D-active ($d\_R\&D$) and whether it is a producer or supplier of environmental technology ($ECPROD$). The latter control especially addresses the concern that environmental R&D may also be spent by firms to develop new, e.g. energy-saving, products or pollution control technologies to be sold to other companies. That is, we want to control for the fact that producing such environmental technology may be the core business of some firms. The firms' patent stock ($PATSTOCK$) is included to control for the firms technological capabilities. We calculate the firms' patent stock as a perpetual inventory of patent applications with a constant depreciation rate of 15 percent, as is common in the literature (Griliches and Mairesse 1984). We also account for the fact whether the firm is part of an enterprize group ($GROUP$). Additionally, we control for structural differences between Eastern and Western Germany that may affect the likelihood to react to regulatory pressure. Firms located in Eastern Germany ($EAST$) may show differences due to historical developments and due to extensive general subsidy programs to foster innovation in Eastern Germany (see for instance Czarnitzki (2006)). Finally, we distinguish 17 different sectors. Table A.1 in the Appendix shows the distribution of firms over these sectors.

4.4 Descriptive Statistics

Table 3 presents summary statistics for the outcome and control variables distinguishing between the treated and non-treated firms. As can be seen, several means of the control variables are significantly different between the treated firms and the control group only slightly varying with the definition of the treatment (REG or SUB). For instance, regulation-affected firms are on average larger and are active in more concentrated industries. Further, they are more often part of a group and have a slightly lower labor productivity. Interestingly, if the treatment is defined based on a subsidy receipt, then treated firms are more likely to be located in Eastern Germany and more likely to conduct R&D on a continuous basis. With respect to the outcome variables, we also do see some significant differences in means. However, as argued above, it would be invalid to conclude that these differences were due to compliance efforts. Likewise, the higher average investment in innovation-related physical assets and other non-innovation related investment in the group of subsidized firms does not necessarily mean that this higher investment was caused by the subsidy. The analysis presented in the following aims at identifying the treatment effects taking the non-randomness of the treatment into account.

Table 3: Descriptive Statistics

		Control Group n = 2,177		**treatment = REG** n = 179			**treatment = SUB** n = 165		
		Mean	Std. Dev.	Mean	Std. Dev.	t-test	Mean	Std. Dev.	t-test
Outcome Variables:									
PROJECTS	#	7.713	44.843	7.877	20.574		10.285	31.535	
INNO_R&D	T €	374.325	1,739.072	309.982	1,221.224		336.667	1,519.585	
INNO_INV	T €	340.474	1,363.726	371.651	1,238.704		573.612	1,884.779	**
INNO_TOTAL	T €	882.077	3,448.380	783.249	2,549.019		1,389.042	4,576.837	**
INNO_NET	T €	751.439	3,186.656	452.402	1,189.564		968.802	3,638.517	
INV	T €	1,824.727	6,395.822	2,120.540	6,298.247		4,023.239	10,149.23	***
PRODUCT_INNO	dummy	0.432	0.496	0.559	0.498	***	0.564	0.497	***
PRODUCT_LEAD	dummy	0.429	0.495	0.486	0.501	*	0.479	0.501	
FAIL_INNO	dummy	0.049	0.215	0.061	0.241		0.055	0.228	
Control Variables:									
log_CAP	assets/sales	-1.394	1.925	-1.218	1.833		-1.077	1.771	**
log_LAB	# empl.	3.867	1.558	4.149	1.415	***	4.226	1.600	***
log_MAT	cost/sales	-0.984	0.838	-0.933	0.569		-1.090	0.955	*
log_AGE	years	3.153	0.902	3.105	0.939		3.109	0.892	
LABPRO	sales/empl.	0.296	2.079	0.191	0.213		0.264	0.735	
HHI	index	468.920	761.949	571.980	802.843	**	487.835	758.889	
ECPROD	dummy	0.215	0.411	0.419	0.495	***	0.333	0.473	***
d_R&D	dummy	0.472	0.703	0.514	0.648		0.552	0.702	*
PATSTOCK	dummy	2.170	29.646	1.129	6.040		1.221	8.374	
EAST	dummy	0.331	0.471	0.296	0.458		0.400	0.491	**
GROUP	dummy	0.319	0.466	0.380	0.487	**	0.327	0.471	

***(**,*) indicate a significance level of 1% (5%, 10%).

5 Econometric Results

5.1 Probit Models on the Selection into Treatment

As described above, in order to apply the matching estimator, we first estimate a probit model to obtain the predicted probability of having introduced a policy-induced environmental innovation. We estimate two different specifications, that is one for each definition of the treatment. Table 4 presents the results from this exercise. We find larger firms and more material and energy-intensive firms to be more likely to introduce regulation-induced environmental technology. Firm age and labor productivity are negatively associated with regulation-induced environmental innovations, while producers of environmental technologies are more likely to be selected into the treatment REG. Larger firms in terms of employees and continuously R&D-active firms are more likely to have introduced a subsidy-supported environmental technology. Firms in Eastern Germany are more likely to introduce an environmental innovation initiated by a subsidy. Group membership is positively significant in model 1, but not in model 2. Finally, it turns out that the industry dummies are jointly significant for the selection into both treatments.

5.2 The Matching

As mentioned before, a necessary condition for the validity of the matching estimator is common support. In our case, this condition is introduced for all our firm pairs. Table 5 shows the results of the NN matching. All control variables are well balanced after the matching so that we can conclude that the matching was successful in the sense that a suitable nearest neighbor was found for each treated firm. The only variables for which there is a significant difference in means after the matching are some of the outcome variables. This difference can be attributed to the respective treatment. However, it turns out that the effects of the treatment on the outcome variable depend on the definition of the treatment. The results for the treatment (REG) are presented on the left-hand side of table 5.

As can be gathered from the table, mean values for $INNO\_R\&D$ and $INNO\_INV$ are significantly lower for treated firms. This also translated into a significant over-

Table 4: Probit Estimation Results on the Selection into Treatment (2,521 obs.)

	TREATMENT	
	Model 1: REG	Model 2: SUB
log_CAP	0.032	0.027
	(0.027)	(0.034)
log_MAT	0.066**	-0.036*
	(0.031)	(0.021)
log_LAB	0.060***	0.083***
	(0.013)	(0.026)
log_AGE	-0.042***	0.004
	(0.001)	(0.115)
$LABPRO$	-0.229	-0.001
	(0.342)	(0.008)
$ECPROD$	0.447***	0.250***
	(0.009)	(0.040)
HHI	-0.001***	-0.001
	(0.001)	(0.001)
$EAST$	-0.124***	0.171**
	(0.035)	(0.078)
$d\_R\&D$	-0.064	0.184*
	(0.139)	(0.100)
$PATSTOCK$	-0.005**	-0.002***
	(0.003)	(0.001)
$GROUP$	0.085***	-0.109
	(0.032)	(0.122)
Log pseudolikelihood	-600.327	-554.474
Joint sign. of ind. dummies	7.51*	18.52***
LR $\chi^2(27)$:	91.24***	109.74***

***,** ,* indicate a significance level of 1%, 5%, 10%.
Clustered standard errors ($EAST$) presented in parentheses.
The models include a constant and 16 industry dummies.

all innovation spending and particularly net innovation spending ($INNO\_NET$). This may suggest a partial crowding out of non-environment-related innovative activities. The magnitude of the crowding out, that is the average treatment effect on the treated (ATT), is the difference between the means. The ATT is higher for R&D than for physical innovation investments and amounts to about 617 thousand euros. Regulation-affected firms thus spend significantly less on internal R&D than their matched control group. For the total innovation expenditure this difference amounts to 833 thousand euros in the respective year, on average. For the adjusted $INNO\_NET$ which is net of cost due to the environmental innovation the ATT is slightly larger with about 978 thousand euros. Note that this is considerably more than the average cost of introducing an environmental technology of 401 thousand euros. These results may thus imply that the average firm in our sample reduced its overall innovation budget by more than the cost related to the environmental innovation project. For the number of innovation projects we do not find a significant difference between the groups. This may indicate that firms reduce the scale rather than the scope of their R&D projects. As expected, investment in non-innovation related physical assets are not subject to a crowding out. When we consider subsidies as the treatment we no longer find such a crowding out effect, as can be seen on the right-hand side of Table 5. Although we see that the mean values for several of the outcome variables are higher in the treated group, the difference is not statistically significant once we account for the fact that we had been drawing from the control group with replacement. Thus, subsidized firms also do not seem to invest significantly more than other firms due to the receipt of public money.

Table 5: Matching Results

		treatment = REG					treatment = SUB				
		non-treated n = 179		**treated** n = 179		t-test$^{\diamond}$	**non-treated** n = 164		**treated** n = 164		t-test$^{\diamond}$
		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Outcome Variables:											
PROJECTS	#	7.793	16.504	7.877	20.574		6.226	16.328	10.329	31.626	*()
INNO_R&D	T €	972.106	3,031.029	309.982	1,221.224	**(**)	423.579	1,931.085	336.707	1,524.24	
INNO_INV	T €	680.224	2,176.982	371.651	1,238.704	* ()	331.659	1,425.572	575.098	1,890.455	*()
INNO_TOTAL	T €	1,665.338	4,898.008	783.249	2,549.019	**(*)	960.726	3,882.869	1,393.976	4,590.415	
INNO_NET	T €	1,493.554	4,760.614	452.402	1,189.564	***(**)	816.718	3,557.378	971.478	3,649.498	
INV	T €	1,848.72	5,843.183	2,120.540	6,298.247		3,185.692	11,355.49	4,040.363	10,177.92	
PRODUCT_INNO	dummy	0.542	0.500	0.559	0.498		0.549	0.499	0.561	0.498	
PRODUCT_LEAD	dummy	0.520	0.501	0.486	0.501		0.433	0.497	0.476	0.501	
FAIL_INNO	dummy	0.061	0.241	0.061	0.241		0.024	0.155	0.055	0.228	

***,**,* indicate a significance level of 1%, 5% 10%.

Control variables (all balanced) not presented. $^{\diamond}$t-tests of differences in means based on Lechner-adjusted standard errors in parentheses.

Table 6: Sensitivity Analysis

	Average Treatment Effects on the Treated (ATT) treatment = REG				
	NN	**2NN**	**NN Caliper**	**2NN Caliper**	**Kernel**
$INNO\_R\&D$	-662.124	-396.415	-534.012	-342.024	-224.405
$INNO\_INV$	-308.573				
$INNO\_TOTAL$	-882.089	-502.021	-779.062	-468.145	-450.468
$INNO\_NET$	-1,041.152	-673.427	-939.922	-641.488	-596.552

ATT presented if significant at least at 10% level.

6 Sensitivity Analysis

To test the sensitivity of our results to specific features of our empirical strategy, we perform a series of alternative matching estimators that share the beneficial properties of non-parametric treatment effect models. Table 6 compares the average treatment effects (ATT) obtained from the NN matching with the results of the two-NN matching, the caliper matching and the kernel matching (Epanechnikov kernel). The caliper is defined such that the largest percentile of the Mahalanobis Distance distribution is dropped from the sample. As can be seen in the table, the estimated ATT varies across these different models. The direction of the effects and their relative magnitude, however, is quite comparable between the different matching approaches.

Based on these results, we conclude the 2NN matching with caliper provides results that are well within the middle of the bandwidth of the range of outcomes.

Therefore, we use the results from the 2NN method for testing whether the average treatment effects differ between different groups of firms. Financially constrained firms, for instance, that have limited access to additional financing may face a stronger crowding out compared to firms that can obtain additional funds from external sources. Likewise, the regulatory burden may be comparatively higher for smaller firms. To test these hypotheses we first calculate the individual treatment effects as the difference between the overall outcome variables of the treated firms and the control firms ($j = 2$) as follows:

$$ATT_i = Y_i - \frac{1}{N}\Sigma_{j=1}^{N} Y_j^c \tag{6}$$

Table 7: Average Treatment Effects on the Treated by Groups

		treatment = REG				
		GROUP = 0		GROUP = 1		t-test
GROUP		ATT	Std. Err.	ATT	Std. Err.	
		$INNO\_R\&D$				
SME	< 250 emp.	288.167	3,285.414	-428.290	1,962.223	**
$TOPRATING$	> 75%	-459.707	2,336.690	350.564	2,325.267	**
$YOUNG$	< 19 yrs.	-236.312	2,544.757	-286.818	2,095.495	
		$INNO\_NET$				
SME	< 250 emp.	425.579	3,039.143	-963.413	4,267.835	**
$TOPRATING$	> 75%	-1,033.115	4,408.007	573.132	2,318.255	**
$YOUNG$	< 19 yrs.	-544.616	3,953.533	-749.674	4,186.421	

We then divide the sample into groups, calculate the means of ATT_i and perform t-tests on the differences in the ATT between groups. The upper panel in Table 7 shows that the treatment effect on $INNO\_R\&D$ is significantly larger for small firms with less than 250 employees. These findings are in line with insights from the literature on financing constraints for innovation that identified SMEs to be more likely to face financing constraints compared to larger firms. Likewise, relatively younger firms in our sample (younger than the median) show a higher treatment effect for net innovation expenditure. However, the difference is not statistically significant. As a more direct measure for access to financing, we split the sample based on the firms' credit rating. Firms with outstanding credit ratings should be able to raise funds in the financial markets at the best possible interest rates independent of the type of investment project. Indeed, we find that for firms with a credit rating in the top 25%, that is in the range between 100 and 193 ($RATING \in [100, 600]$), the ATT is even positive and significantly different from the negative ATT of firms with worse credit ratings. In other words, we find a negative treatment effect for all firms but those with the best credit ratings in our sample.

7 Conclusion

The presented analysis set out to complement the few existing studies on potential crowding out effects of policy-induced environmental innovation on firms' conventional innovative activities. Since innovation in general is a crucial driver of economic growth and competitiveness, a potential crowding out of other innovation could be a barrier to competitiveness and economic growth in the long-run adding to the cost of fighting environmental damage. Using different treatment effect models, we estimated the effects of regulation-induced environmental innovation on the firms' non-green innovative activities. We find indeed evidence for some crowding out of the firms' R&D and total innovation expenditure net of those costs due to the environmental innovation. On the other hand, we find such effects on the number of ongoing R&D projects, investments in innovation-related and other fixed assets nor on the outcome of innovation projects. Thus, firms may rather scale down investment in areas like R&D that are not directly related to current production, but are rather long-term oriented and less certain in terms of returns. While the direction and significance of these findings is robust to the estimation method, the magnitude of the estimated average treatment effects varied according with an average estimate of 432 thousand euros within a bandwidth between 225 and 662 thousand euros. Interestingly, the estimated average reduction in R&D is quite close to the reported annualized cost for the introduced environmental technology of about 401 thousand euros. We also observed differences in the magnitude of the estimated treatment effect between different groups of firms. Larger firms experience significant smaller treatment effects and firms with very good credit ratings even show a positive treatment effect, on average. This points to the conclusion that firms that already face financing constraints may have to scale down current R&D to a greater extent than less constrained firms.

The observed effects may be due to short-term budget re-allocation from R&D to compliance efforts. As R&D expenditures are to a large part spent on researchers' wages and we assume wages to be rather fixed in the short-term, we can only hypothesize that firms may re-allocate R&D employees' tasks. However, affected firms were not more likely to cancel ongoing projects nor did they report lower expectations regarding the market introduction of new products as compared to the control group. Moreover, for firms with subsidy-induced environmental innovations, no crowding out of non-green R&D is found. While these results support the idea that a policy mix of market-based mechanisms, direct financial support, and command-and-control regulation may yield most efficient environmentally beneficial technological advances, they also suggest that the observed effects may be rather short-term and not detrimental for affected firms' innovation performance.

However, these results should be interpreted with the study's limitations in mind. The ideal experiment would require to observe firms and how regulation induces environmental investments over time. Additionally, the present study abstracted from making welfare assessments as the unit of observation was the firm. Accounting for the public costs associated with the provision of environmental subsidies appears notwithstanding crucial for the evaluation environmental policies, especially in a inter-generational context (Leach and Laurent-Lucchetti 2011) as well as considering the global opportunity cost of climate change policy (**?**).

Future research would therefore benefit from panel data observing R&D activities and regulatory changes over a longer period of time, and ideally, even at the project level. Such data would allow to assess the impact of regulation-induced environmental technology on the long-run innovation performance in product markets and hence on firms' overall competitiveness. In case of a substantial crowding out of competitiveness-enhancing R&D, one would expect to observe a reduced overall innovation performance of affected firms. Moreover, while there might be a crowding out in the sense that "other R&D" is reduced if firms devoted effort to introducing environmental innovations, this may also be the result of rational, profit maximizing firms switching R&D resources from established, for instance, more energy- intensive technologies, to greener technologies. If the crowding out affects merely dirty technologies we would expect no long-lasting effect on innovation and firm performance. We therefore strongly encourage further research that tackles the challenge to study the nature and heterogeneity of environmental regulation, subsidy programs and new technologies.

Figure 1: Cumulated number of Regulations in Germany

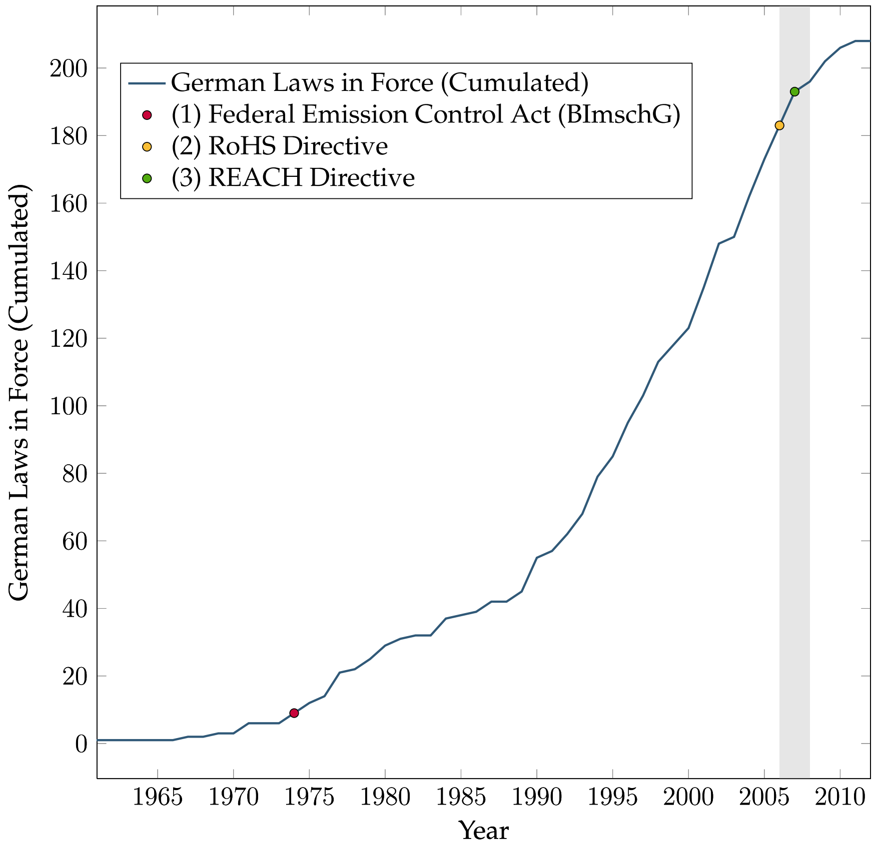

Table A.1: Sector Distribution

		by treatment		full sample	
NACE Codes	**Sector Description**	**REG**	**SUB**	**%**	**Freq.**
10-12	Food, beverages, and tobacco products	6.92	4.62	5.16	130
13-15	Textiles, wearing apparel, and leather	2.44	2.44	3.25	82
16-17	Wood and paper products	5.13	5.98	4.64	117
20-21	Chemical and pharmaceutical products	9.35	3.74	4.24	107
22	Rubber and plastic products	5.31	7.08	4.48	113
23	Other non-metallic mineral products	6.33	6.33	3.13	79
24-25	Basic metals, fabricated metal products, except machinery and equipment	5.91	6.33	9.40	237
26-27	Computer, electronic and optical products, electrical equipment	16.39	4.92	9.68	244
28, 33	Machinery and equipment n.e.c., repair and installation of machinery and equipment	5.97	5.60	0.63	268
29-30	Motor vehicles, trailers and semi-trailers, other transport equipment	4.21	4.21	3.77	95
31-32	Furniture and other manufacturing	6.72	0.84	4.72	119
35, 19	Electricity, gas, steam and air conditioning supply, coke and refined petroleum products	5.83	11.65	4.09	103
36-39	Water Supply, sewerage, waste management and re-mediation activities	9.80	6.86	8.09	204
41-43	Construction	6.77	5.41	2.94	74
45-47	Wholesale and Retail trade, repair of motor vehicles and motorcycles	4.61	2.63	6.03	152
49-53	Transportation and storage	7.79	19.91	9.16	231
18, 58-60	Printing and reproduction of recorded media, publishing, motion picture, video and television programme production, sound recording, broadcasting activities	1.81	0.36	6.58	166
Total		100	100	100	2,521

Table A.2: Effective laws, ordered by frequency of citation

No.	Acronym	Description
1	BImschG/(BImschV)	Federal Emission Control Act/(Directives)
2	RoHS	European Directive on Restriction of hazardous substances
3	REACH	European Directive on Registration, Evaluation, Authorisation and Restriction of Chemicals
4	EnEV	Energy Saving Directive (for Buildings)
5	TA Luft	Technical Guidance on Clean Air (directive for BimschG)
6	WHG	Water Resource Law
7	VOC Directive	Directive to Limit Volatile Organic Compounds (VOC) Emissions
8	WEEE	European Directive on Waste of Electrical and Electronic Equipment
9	EEG	Renewable Energy Law
10	VerpackV	Packaging Ordinance
11	ElektroG	Electrical and Electronic Equipment Act (German implementation of the WEEE Directive)
12	GefStoffV	Hazardous Substances Regulation
13	KrW-/AbfG	Recycling and Waste Management Act
14	Euro 5	Euro 5 Air Emission Standard for Cars
15	TA Lärm	Technical Guidance on Noise Mitigation
16	EU ETS	European Emission Trading Scheme for CO_2
17	ISO 14001	ISO 14001 Environmental Management Standard
18	Decopaint Directive	European Directive on VOC limitation in colors and paints
19	EUP	European Energy-using Products Directive
20	UschadG	Environmental Damage Act
21	EnWG	Energy Management Act
22	BBodSchG	Federal Soil Protection Act
23	KWKG	Combined Heat and Power Act
24	EnEG	Energy Saving Act
25	BNatSchG	Federal Nature Conservation Act
26	DüMV	Fertilizer Act
27	Deponie-RiLi	European Landfill Directive
28	MarPol	International Convention for the Prevention of Pollution from Ships
29	TA Siedlungsabfall	Technical Guidance on Municipal Waste
30	DepV	German Landfill Directive
31	EnergieStG	Energy Taxation Act
32	StromsteuerG	Electricity Taxation Act
33	Euro 4	Euro 4 Air Emission Standard for Cars
34	Wasserrahmenrichtlinie	Water Framework Directive
35	Abwasserrahmenrichtlinie	European Wastewater Directive
36	GSchV	Water Protection Directive
37	ErsatzbaustoffV	Directive on Substitute Materials for Buildings
38	EG-AbfVerbrV	European Waste Shipment Directive
39	AbfAblV	Waste Storage Directive
40	STrSchG	Radiation Protection Act
41	VO(EG) Nr. 842/2006 (FKW)	European Directive on Certain Fluorinated Greenhouse Gases
42	EEWärmeG	Renewable Energy Heat Act

Appendix A: Instrumental Variable Regressions

As an alternative to the treatment models presented before, Table A.3 shows the results from a two-stage least squares estimation taking into account the endogeneity of the treatment variables. For the purpose of the IV regressions, we construct instrumental variables (IV) that are correlated to the potentially endogenous variable, i.e. the treatment indicators, but exogenous to the individual firm's innovation activity. For REG we derive three IV. The first $(IV1\_REG)$ is a regional measure of woodland area per inhabitant at the four-digit regional code which divides Germany in 413 districts. We would expect industrial density to be lower in areas with a higher woodland area per inhabitant. Firms in such regions compared to firms in densely populated areas should be less likely to be affected by regulation as several environmental laws require stricter environmental specification and regulation in latter areas (see for instance the Federal Emission Control Act). The second $(IV2\_REG)$ is the average frequency of regulation-affected firm by size class.[20] Thereby we differentiate between Eastern and Western Germany because of the structural differences between the regions. The third $(IV3\_REG)$ captures the average frequency by industry. Industries are classified as described in Table A.1. Like in the previous case we also distinguish between Eastern and Western Germany.

In a similar fashion, the first IV for SUB is constructed from an average frequency of effective environmental subsidies in a four-digit geographical district $IV1\_SUB$. The second IV is derived from a proximity measure to high ways $IV2\_SUB$. In a region with a dense weak highway infrastructure, we would expect a higher occurrence of subsidies. Third, we take the unemployment percentage in a four-digit district of an indication on the liquidity of the public sector in that region. If unemployment is high fewer subsides may be granted that are specific for environmental technology. The same set of control variables as in the selection equation for the propensity score estimation is included. We limit the presentation of the model results to the outcome variable ($INNO\_R\&D$). The

[20]We construct five classes based on the firms' workforce size ranging from 1-50 employees, from 51-150 employees, from 151-250 employees, from 251-500 employees and larger than 500 employees, respectively.

left hand side of the table presents the results for the case of regulation-induced technology adoption while the right hand side shows the results for the subsidy-backed case. The test statistics show that the IV fulfil the commonly used criteria for valid instruments. The instruments are relevant at the first stage (see F-Test of joint significance of the excluded instruments in the first stage at the bottom of Table A.3) and the Hansen J test statistic, i.e. the heteroscedasticity-robust version of the Sargan test rejects overidentification. The coefficient of REG is negative and significant in the second stage in line with the matching results. The coefficient of SUB, on the other hand, is positive albeit fails to pass the threshold for being statistically significant at the 10% level. Thus, both models provide results that are in line the matching results.

Table A.3: Instrumental Variable Regressions on $ln[INNO\_R\&D+1]$ (2,521 obs.)

	treatment = REG				**treatment = SUB**			
	1st stage		**2nd stage**		**1st stage**		**2nd stage**	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Variables:								
$REG \mid SUB$			-3.340	(1.562)**			1.081	(0.782)
log_CAP	0.004	(0.003)*	0.028	(0.020)	0.002	(0.003)	0.011	(0.017)
log_MAT	0.006	(0.004)	-0.035	(0.043)	-0.004	(0.006)	-0.047	(0.041)
log_LAB	0.001	(0.004)	0.475	(0.035)***	0.010	(0.004)**	0.441	(0.031)***
log_AGE	-0.006	(0.006)	-0.017	(0.046)	-0.001	(0.006)	0.001	(0.042)
$LABPRO$	-0.002	(0.001)*	0.034	(0.017)**	0.001	(0.001)	0.038	(0.019)**
HHI	0.001	(0.001)	0.001	(0.001)	-0.001	(0.001)***	0.001	(0.001)*
$ECPROD$	0.069	(0.015)***	0.548	(0.142)***	0.035	(0.013)***	0.285	(0.088)***
$d\_R\&D$	-0.012	(0.007)	1.913	(0.075)***	0.018	(0.007)**	1.927	(0.069)***
$PATSTOCK$	-0.001	(0.001)	0.007	(0.004)*	-0.001	(0.001)	0.008	(0.004)**
$EAST$	0.022	(0.014)	-0.021	(0.086)	0.026	(0.017)	0.006	(0.073)
$GROUP$	0.002	(0.014)	0.351	(0.102)***	-0.013	(0.012)	0.336	(0.091)***
$IV1\_REG$	1.035	(0.285)***			0.969	(0.152)***		
$IV2\_REG$	0.983	(0.247)***			-0.001	(0.001)**		
$IV3\_REG$	-0.001	(0.001)**			-0.004	(0.002)**		
$IV1\_SUB$								
$IV2\_SUB$								
$IV3\_SUB$								
Cragg-Donald F-test	10.553***				24.582***			
Hansen J			4.011				0.459	
R^2			0.63				0.71	
Joint sign. industries			232.87***				254.16***	

Robust standard errors in parentheses. ***,**,* indicate a significance level of 1%, 5%, 10%.
Intercepts and industry dummies not presented.

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