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The Link Between R&D Subsidies, R&D Spending and Technological Performance

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Non–technical summary

The importance of R&D as a main factor of sustainable growth in highly industrialized economies is undisputable among economists. In recent years a growing gap in the levels of research investment between Europe and the US or Japan has been observed. European governments fear the negative consequences for the long–run technological performance, growth and employment potential. For this reason, the 2002 EU member states agreed on the so–called Barcelona objectives. On this basis, the "Action Plan for Europe" has been proposed: the European R&D expenditure should be increased from currently 1.9% of GDP to 3.0% by 2010, where two thirds should be financed by the business sector, as its R&D spending is currently lagging behind the U.S. and Japan. In order to achieve this goal, national governments are requested to reinforce their national technology programs to support R&D in the business sector.

In line with that task, this paper analyzes the effects of public R&D project funding on private R&D expenditure and subsequently the effect of the publicly induced R&D spending on the patenting behavior of firms empirically. The presumed mechanism behind the European Action Plan is that public incentives are expected to stimulate the private R&D engagement and that such additionally induced R&D activities lead to new products and processes improving the European technological performance. This is by no means clear: every firm has an incentive to apply for subsidies and to substitute public funding for private research investment. If full crowding–out effects occur, public incentives would not lead to any improvement of technological performance. Furthermore, it is not clear whether additional R&D projects that have been conducted due to the receipt of subsidies lead to successful results. Assuming that firms have some R&D project portfolio to choose from, they will obviously start with those projects promising the highest expected returns. Hence, publicly funded R&D projects will show lower expected returns than purely privately financed ones; possibly due to a higher outcome uncertainty. Thus, even if no crowding–out effects take place, the technological and economic benefits of public funding are questionable. The central contribution of this paper is the empirical investigation of the link between subsidies, the input side of the innovation process and the impact on technological performance in a system of equations.

We use a large sample of German R&D performers from the manufacturing sector to test the presumed mechanisms of the European Action Plan. Our sample covers 3,799 firm–year observations of which 588 received subsidies. Conducting a treatment effects analysis to investigate the crowding–out versus the complementarity hypothesis yields that we can reject full as well as partial crowding–out effects. In fact, public incentive schemes seem to accelerate the R&D spending in the business sector. In a second step, we implement the results of the treatment effects analysis into a patent production function, where R&D investment is disentangled into two components: on one hand, the purely privately financed part of the total R&D budget that firms would have spent in the absence of subsidies and, on the other hand, the additionally induced R&D expenditure due to subsidies. We find that both the purely financed R&D and the estimated treatment effect show a positive impact on the patenting behavior of firms. Hence, we do not have to reject the presumed mechanism in the European Action Plan. Public policy initiatives indeed foster the private R&D engagement, so that meeting the Action Plan's 3% goal can actually be promoted by public policy. Furthermore, it contributes to the ultimate goal of the Action Plan, namely to increase Europe's technological performance, as the regression analysis reveals that even the publicly stimulated additional R&D leads to an increased patenting activity.

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Abstract

This paper analyzes the effects of public R&D funding on R&D expenditure and patenting behavior of German firms. The main focus is the direct impact of subsidies on R&D and the indirect effect on innovation output measured by patent applications. We distinguish the productivity of purely privately financed R&D and additional R&D induced by public incentive schemes. For this, a treatment effects analysis is conducted in a first step. The results are implemented into the estimation of a patent production function. It turns out that both purely privately financed R&D and publicly induced R&D show a positive productivity.

Keywords: R&D, Subsidies, Patents, Treatment Effects
JEL–Qualification: C14, C30, H23, O31, O38

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1 Introduction

The importance of R&D as a main factor of sustainable growth in highly industrialized economies is undisputable among economists. In recent years a growing gap in the levels of research investment between Europe and its main trading partners has been observed. For instance, the gap in research investment between the European Union and the United States is already in excess of EUR 120 billion per year and widening fast, with alarming consequences for the long–run technological performance and, hence, for growth and employment potential. For this reason, the 2002 EU member states agreed on the so–called Barcelona objectives in order to bridge the growing gap. The objective is to increase the average gross expenditure on research and development (GERD) from 1.9% of GDP to 3.0% by 2010, of which two thirds should be funded by the private sector. The research investment slack in the business sector is seen as the major cause for the growing R&D gap. While for some European economies like Finland, the threshold values are already passed, Germany's GERD as percentage of of GDP was at 2.5% in 2001.

Based on the Barcelona objectives, the European Commission came up with the "Action Plan for Europe" that proposes the national governments to reinforce their technology policy towards a stimulation of R&D spending of the business sector (see European Commission, 2003). The presumed mechanism behind the European Action Plan is that public incentives are expected to increase the private R&D engagement in the business sector and that such additionally induced R&D activities lead to new products and processes improving the European technological performance. This is by no means clear: First, every firm has an incentive to apply for subsidies and to substitute public funding for private research investment. If full crowding–out effects occur, public incentives would not lead to any improvement of technological performance. Second, it is not clear a–priori whether additional R&D projects that have been conducted due to the receipt of subsidies lead to successful results. Assuming that firms have some R&D project portfolio to choose from, they will obviously start with those projects promising the highest expected returns. Hence, publicly funded R&D projects will show lower expected returns than purely privately financed ones. Although those may exhibit large social benefits, their associated uncertainty of outcome will presumably be higher. Thus, even if no crowding–out effects take place, the technological and economic benefits of public funding are questionable.

In this paper, we analyze the mechanisms as presumed in the European Action Plan at the firm level: the link between public funding and R&D input, in the first step, and the relationship between R&D input and technological performance in second step. Technological performance is measured by patent applications, because this is a widely accepted indicator on countries' technological potential and the patent outcome is depending on successfully completed research projects.

The essential contribution to the literature is that we especially take into account the effect of additionally induced R&D due to public incentive schemes on the firms' patent productivity. Beforehand, researchers either analyzed the input side or the output side of the innovation process. In this study, however, the direct impact of subsidies on innovation input and the indirect effect of subsidies on innovation output through possibly increased R&D spending is explicitly modelled in a system of equations.

Positive effects of public funding on private R&D and a positive patent outcome of the additionally induced R&D are necessary prerequisites for a successful improvement of Europe's technological performance and a positive assessment of technology policy. The following section describes and motivates the setup of our empirical model. Section 3 presents our estimation strategy on the basis of our model setup including a brief literature review. The data and variables used to test the presumed relationships of the Action Plan are introduced in Section 4. The estimation results are discussed in Section 5 and Section 6 concludes.

2 Model Setup

There are clear economic rationales behind supporting private R&D: The level of privately financed R&D activities is lower than socially desired, because R&D has the characteristics of a public good and generates positive external effects, which cannot be internalized (see Arrow, 1962). Thus, there may be projects that would have positive benefits to society, but do not cover the private cost. As a result, these projects are not carried out and the quantity of innovations is below the socially desirable level. This theory is the main reason for governments to subsidize private R&D projects. Public funding reduces the price for private investors and thus the innovations are carried out. However, a firm has always an incentive to apply for public R&D support, even if the private expected return is positive and it could perform the R&D projects using its own financial means. If public support is granted, the firm then might simply substitute public for private investment. This possible crowding–out effect between public grants and private investment has to be taken into account when public authorities decide on the level of their engagement in R&D support programs. The crowding–out versus the stimulation hypothesis is the first mechanism to be investigated on the background of the European Action Plan 2010. Only if full crowding–out effects can be rejected, total R&D activity is increased by governmental incentive schemes.

In the second step, we investigate whether the additional R&D induced by public policy leads to benefits in terms of technological performance. In case of profit maximizing companies, we can assume that firms first conduct those projects from their research portfolio that have highest expected profits. The government's aim with granting subsidies is to stimulate additional R&D projects that possibly have high social returns, but do not cover private cost.[1] Suppose a firm decided to perform five different R&D projects with positive expected profits. In case of the receipt of a subsidy, the government wants the firm to launch a sixth project that had not been conducted in the absence of public support. However, it is not clear if this additional projects leads to positive benefits for society. If the firm initially had considered not to conduct this project due to low or even negative private expected return, the project could be associated with a high risk of failure. Even if the government expects high social returns, it is questionable whether the risk of failure is appropriately taken into account in the Governments' decision process. Hence, even if no crowding–out effects occur, the publicly induced additional R&D may not lead to a significant improvement of technological performance, because a large share of such projects bear high risk and might fail. This second mechanism is to be tested, if the ambitious task of the European Action Plan wants to be fulfilled by 2010. A model that can be used to test these relationships empirically may take following form:

First, we test for crowding–out effects by conducting a treatment analysis. We estimate how much R&D subsidized firms would have conducted, on average, if they had not been funded. This can be expressed by the average treatment effect on the treated

$$\alpha^{TT} = E(\alpha_i) = E(R\&D_i^T|S = 1) - E(R\&D_i^C|S = 1) \tag{1}$$

where $R\&D_i^T$ indicates the R&D expenditure in case of treatment, $R\&D_i^C$

[1]Direct R&D project funding is the most important instrument in Germany's technology policy. There are no R&D tax credits in place.

the counterfactual situation, and $S \in \{0, 1\}$ indicates the treatment status (receipt of subsidy). Thus the empirical test of the first mechanism implied by the European Action Plan is whether $\alpha^{TT} > 0$. Our estimation strategy will be outlined in Section 3.

Second, even if we find evidence for $\alpha^{TT} > 0$, it is not clear that the public efforts lead to new technologies. In case of frequent failures of the additional R&D projects, public policy would not improve the development of new products and processes. In order to assess the effect of R&D on new technologies, we analyze patent applications in this second step. Patents are a widely accepted indicator for technological performance and international comparisons of such (see Griliches, 1990, or OECD, 1994). Unfortunately, one cannot observe the breakdown of R&D activity into purely privately financed projects and those projects that have been induced by public policy. Note that it is not sufficient to split the R&D expenditure into the amount of the subsidy and the private proportion, because if a subsidy is granted in Germany it is given as matching grants, that is, the firm can apply with a specific project and in case of successful review process, the Government pays some share of the total cost, usually between 30 and 50%. So it is important to disentangle the R&D expenditure into $R\&D_i^C$ and α_i as indicated in eq. (1). The first term denotes the research engagement of the firm in the absence of a treatment and α_i comprises of the subsidy and the additionally financed R&D of the firm. Thus, the second equation to be estimated can be written as

$$PATENT_i = f(R\&D_i^C, \alpha_i, \text{other firm characteristics}) \qquad (2)$$

The empirical assessment of the second mechanism, namely that public policy incentive schemes create knowledge and improve the technological performance, amounts to testing whether α_i is significantly positively influencing the patent outcome.

3 Literature Review and Estimation strategies

Literature on the crowding–out effects

The evaluation of public funding is not new in industrial economic context. David et al. (2000) and Klette et al. (2000) survey the existing literature on the effects of public R&D grants on private R&D spending at different aggregation levels. They conclude that the majority of the considered studies find a complementary relationship of privately and publicly financed

R&D. However, one major criticism of David et al. and Klette et al. on former studies is the disregard of a possible selection bias. If, for example, the government follows a picking–the–winner strategy, it will subsidize those firms that are highly innovative and successful. Hence a mean comparison of R&D expenditure between recipients and non–recipients would yield biased results, as such firms may have very different characteristics. Since then, some studies take the selection bias into account: Busom (2000) applies Heckman–type selection models and rejects full-crowding out, but finds partial crowding–out effects for Spain; Wallsten (2000) employs simultaneous equations to model R&D expenditure and subsidies. Using a 3SLS estimator, he finds a substitutive effect of R&D grants from SBIR program in the US; Lach (2002) applies the difference–in–difference estimator and dynamic panel data models for Israel and identifies large positive effects for small firms, but insignificant effects in his full sample; Czarnitzki (2001), Czarnitzki and Fier (2002), as well as Almus and Czarnitzki (2003) employ matching approaches to investigate the impact of public subsidies in Germany, and they reject full crowding–out in Eastern German manufacturing and in the German service sector; Hussinger (2003) explores semiparametric selection models and applies them to a similar dataset used in this paper. She confirms the positive results previously identified with German data; Duguet (2004) employs the matching methodology with a large panel of French firms covering the years 1985 to 1997. Controlling for past public support the firms benefited from, he also rejects the crowding out hypothesis for France. González et al. (2004) investigate subsidies in a panel of more than 2,000 Spanish manufacturing firms and employ a simultaneous equation model. They state that subsidies are effective in inducing firms to invest into R&D, but they induce only slight changes in the level of R&D expenditure. They conclude that in the absence of subsidies, publicly supported R&D projects would be carried out, although in smaller size. However, they do not report crowding–out effects or inefficient use of subsidies. In summary, the majority of recent studies report complimentary effects of public R&D, but crowding–out effects, especially partial ones, cannot be ruled out.

Estimation strategy to assess the crowding–out hypothesis

The modern econometric evaluation techniques have been developed to identify treatment effects when the available observations on individuals or firms are subject to a selection bias. This typically occurs when participants in public measures differ from non–participants in important characteristics.

Popular economic studies are on the benefit of active labor market policies.[2] The literature on the econometrics of evaluation offers different estimation strategies to correct for selection bias (see Heckman et al., 1997, Heckman et al. 1999 for a survey) including the difference–in–difference estimator, control function approaches (selection models), IV estimation and non–parametric matching. The difference–in–difference method requires panel data with observations before and after/while the treatment (change of subsidy status). As our database (to be described in the following section) consists of cross–sections, we cannot apply this estimator. For the application of IV estimators and selection models one needs valid instruments for the treatment variables. It is very difficult in our case to find possible candidates being convincingly used as instruments. Therefore, we choose the matching estimator. Its main advantage over IV and selection models is that we neither have to assume any functional form for the outcome equation nor is a distributional assumption on the error terms of the selection equation and the outcome equation necessary. The disadvantage is that it does only control for observed heterogeneity among treated and untreated firms. However, as we discuss in the next section, we think that our set of covariates allows us to assume that selection on unobservable effects is unlikely.

As said above, we choose a matching estimator to estimate the average treatment effect on the treated as shown in eq. (1).[3] Building on the conditional independence assumption (Rubin, 1974, 1977), one can estimate the counterfactual situation by using a selected group of non–subsidized firms that have similar characteristics X:

$$E(R\&D^C|X, S = 1) = E(R\&D^C|X, S = 0). \tag{3}$$

The construction of the control group depends on the chosen matching algorithm. In this paper, we choose a nearest neighbor matching, that is, for each subsidized firm, we search for the most similar firms in terms of the characteristics X in the potential control group. As X contains several elements, it is virtually impossible to find twin firms that exactly show the same characteristics as the treated firms. A popular method to circumvent this problem of the "curse of dimensionality" is based on Rosenbaum and

[2]See Klette et al. (2000: 479–482) for a discussion of the selection problem in the context of R&D subsidies.

[3]A detailed discussion of the matching methodology is beyond the scope of this paper. See, for example, Angrist (1998), Dehejia and Wahba (1999), Heckman et al. (1998a, 1998b), and Lechner (1999, 2000). A discussion of matching in the context of R&D subsidies can be found in Almus and Czarnitzki (2003).

Rubin (1983). They have shown that it is sufficient to match on the propensity score $P(X)$, that is, the probability to receive subsidies in our case. Using this single scalar measure in the matching routine ensures that the samples of treated and non–treated firms are, on average, statistically not different in X. As the propensity score is not observed, it has to estimated. One precondition for the matching to be consistent is the common support assumption, that is, for each subsidized firm, there has to be a sufficiently similar non–treated firm in the potential control group. In practice, the samples are usually restricted to common support. If, however, the loss of observations is too large, the matching is not appropriate to estimate α^{TT}. See Table 1 for a more detailed description of the matching algorithm used in this study.

The patent production function

The relationship between R&D and patenting has been broadly analyzed in the economic literature since the 1980s. Pakes and Griliches (1984) argue that patents have the advantage to occur at an intermediate stage of the transformation process from R&D input to R&D output. Thereby patents indicate successful R&D and separate this intermediate R&D outcome from the profit generating part of the innovative process.

In the literature, patents are mainly considered as a function of the firms' contemporaneous and lagged R&D expenditure. Hall et al. (1986) analyze the lag structure between R&D expenditure and patenting. They confirm the result of Pakes and Griliches (1984) that there is the strongest weight on the contemporaneous relationship between R&D expenditure and patenting, and they further conclude that the contribution of the observed R&D history to the contemporaneous patent applications is quite small.

Besides R&D, the specification of the patent production function is usually not very rich. R&D expenditure is the most important input factor catching also strategic aspects, and industry dummies and time dummies are usually included in order to control for technology differences among industries (their average patent propensity) and changes in the macroeconomic patenting behavior. Other regressors are rather sparingly used.[4]

The only studies on research productivity measured by patents and tech-

[4]Examples are spill–over measures (cf. Jaffe, 1986, Cincera, 1997); or the book value of firms (cf. Hall et al., 1986)

Table 1: The matching protocol

1.	Estimate the propensity score $P(x_i'\beta)$ and restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group.
2.	Select a firm i that received public R&D funding.
3.	Take the estimated propensity score $P(x'\hat{\beta})$. In many empirical studies one wants to balance the participants and control observations with regard to more characteristics than the propensity score. Firm size is an example. Therefore one uses, additionally to the propensity score, a vector ν (where ν is a subset of X) that contains important matching variables. This variant is called hybrid matching (see Lechner, 1998).
4.	Then one calculates a proper measure of metric distance, e.g. the Mahalanobis distance. Let: $d_{ij} = \left(P(x_i'\hat{\beta}),\ \nu_i\right) - \left(P(x_j'\hat{\beta}),\ \nu_j\right) \quad \forall\ j = 1,\ldots,N^C$ for every combination of the R&D recipient i and every firm from the potential control group j. Then calculate the Mahalanobis distance: $MD_{ij} = d_{ij}\ '\ \Omega^{-1}\ d_{ij} \quad \forall\ j = 1,\ldots,N^C$ to find the nearest neighbor. Ω represents the covariance matrix based on the controls, i.e. firms that did not receive public subsidies.
5.	After calculating the distance, one possibly wants to impose additional restrictions on the neighborhood. For instance, we require that for being a neighbor of participant i, a potential control firm has to be recorded in the same industry classification. Firms in other industries are deleted from the potential control group.
6.	The firm j from the potential control group with the smallest distance serves as control observation in the following outcome analysis. The comparison observation is drawn randomly if more than one firm attains the minimum distance.
7.	Remove the i–th firm from the pool of firms that received subsidies but return the selected control observation to the pool of control observations. This is done because of the relatively limited number of control firms. Using different data, i.e. a larger potential control group, one could also draw without replacement.
8.	Repeat steps 2 to 7 to find matched pairs for all recipients.
9.	Once a control observation has been picked for each subsidized firm, one can calculate the mean difference between the treatment group and the selected control group: $\hat{\alpha}^{TT} = \frac{1}{N^T}\left(\sum_{i=1}^{N^T} R\&D_i^T - \sum_{i=1}^{N^T} \widehat{R\&D}_i^C\right).$ As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t–statistic is biased, because it does not take the appearance of repeated observations into account. Therefore, we have to correct the standard errors in order to draw conclusions on statistical inference. We follow Lechner (2001) and calculate his estimator for an asymptotic approximation of the standard errors.

nology policy are Branstetter and Sakakibara (1998, 2002). They study the performance of Japanese research consortia which are heavily subsidized. Branstetter and Sakakibara investigate if the subsidy, that is, being a member in one of the subsidized research consortia, increases research productivity of Japanese companies with respect to patent applications in the US. In order to do that they, for example, regress the patents on R&D and the consortia dummy in the 1998 paper. Branstetter and Sakakibara find a positively significant coefficient of the consortia dummy, and conclude that the subsidies have a positive impact on research productivity due to spill–over effects that are generated within the consortia. The set up of our model is different: the subsidy affects primarily R&D activity and reveals the benefit only in the second step from R&D projects to patents.

Building on the results of Pakes and Griliches as well as on Hall et al., we use a cross–sectional approach with the contemporaneous R&D expenditure accounting also for the innovative history. As R&D exhibits high adjustment costs, it is quite constant over time, and thus the current R&D spending is also a good approximation of the previous R&D engagement of firms. Jaffe (1986) does also estimate cross–sectional regressions to investigate the relationship between patents and R&D. The most common approach to estimate patent production functions is count data models. In this paper, a negative binomial regression model is chosen to analyze the impact of the two R&D components on the number of patent application.[5] In addition we also estimate a probit model on the propensity to file at least one patent.

4 Data and Empirical Considerations

Our final database results from linking different sources at the firm level. Company information is taken from the Mannheim Innovation Panel (MIP),[6] which is an annual survey conducted by the Centre for European Economic Research (ZEW) on behalf of the German Federal Ministry for Education and Research (BMBF) since 1992. However, many firms are only observed once, because the participation in the survey is not mandatory and many firms are reluctant to publish information voluntarily. For example, in our final sample more than 50% of the companies are only observed once. For this reason, we conduct a pooled cross-sectional analysis rather than a panel–

[5] Panel approaches that address the count data nature of the patent applications and individual effects are provided e.g. by Hausman et al. (1984) and Blundell et al. (2002).

[6] See Janz et al. (2001) for a detailed description of the MIP.

econometric approach.

Information on the direct project funding of the German Federal Government is taken from the PROFI database of the BMBF, which contains information on all civilian R&D projects that have been funded since 1980. Additionally, the database of the German Patent and Trade Mark Office (GPTO) is used. It contains information on all patent applications in Germany since 1979. Linking the PROFI database and the patent database to the MIP required a text field search by firm names and addresses. Finally, some information like the firms' age, legal form and major shareholding are taken from the Creditreform database.[7] Some industry data is taken from the OECD STAN database and from the annual reports from the German antitrust commission.

The combination of the MIP and the PROFI database allows us to identify different categories of firms: first, companies that have received public funding from the German Federal Government, second, companies that have received R&D subsidies from other sources like the German Länder or the European Union and, third, companies that did not receive any public R&D grants. As we are interested in the public funding by the Federal Government, we drop the second group of firms. Hence, the firms in the potential control group are non–funded firms and we can rule–out side effects of other programs, especially those by the EU, that may have led to an underestimation of treatment effects. Our study focuses on R&D performers in the manufacturing sector and takes firms from at least five employees into account. Due to the proposed matching estimator, we drop a very few huge firms that are definitely unique in the economy, and it would not be sensible to construct a control group for such firms. Thus, the study is restricted to firms with 3,000 employees at most. The final sample covers the period from 1992 to 2000 and comprises of 3,779 firm–year observations of which 588 refer to recipients of public R&D funding by the German Federal Government. Table 2 presents the descriptive statistics of all variables used.

Endogenous variables in the first stage of the analysis are the firms' funding status and the R&D expenditure (in million DM) as defined in the Frascati Manual (OECD, 1993). We distinguish two variables: RD_{it} includes the private investment as well as the subsidies. $NETRD_{it}$ is equal to RD net the amount of subsidies.[8] As a further robustness check of our results, we

[7] Creditreform is the largest German credit rating agency.

[8] For convenience we omit the subscript it in the following. All variables are at the firm

Table 2: Descriptive Statistics

# of observations:	funded firms $N^T = 588$		non–funded firms $N^C = 3,191$		mean
variables	mean	std. dev.	mean	std. dev.	difference
$PATENT$	3.52	6.82	1.18	3.45	2.35***
$D(PATENT > 0)$	0.47	0.50	0.26	0.44	0.21***
RD	4.11	5.69	1.76	3.69	2.35***
$RD/SALES$	6.23	7.58	3.13	4.85	3.09***
$NETRD$	3.86	5.60	1.76	3.69	2.09***
$NETRD/SALES$	5.31	6.35	3.13	4.85	2.17***
PS/EMP (lagged)	0.03	0.06	0.02	0.04	0.01***
$\ln(EMP)$	5.67	1.23	5.03	1.34	0.65***
$EAST$	0.36	0.48	0.16	0.36	0.21***
$\ln(AGE)$	2.85	1.33	3.07	1.23	-0.22***
$GROUP$	0.33	0.47	0.12	0.33	0.20***
$FOREIGN$	0.04	0.20	0.01	0.12	0.03***
$CAPCOM$	0.97	0.00	0.94	0.01	0.03***
$EXPORT$	0.32	0.25	0.25	0.23	0.07***
$IMPORT$ (lagged)	0.31	0.22	0.28	0.22	0.03***
HHI (lagged)	0.06	0.08	0.05	0.07	0.01***

*** (**,*) indicate a significance level of 1% (5%, 10%).
The samples also differ significantly in the distribution over industries and time (6 time and 12 industry dummies not presented).

also consider the R&D intensities measured as R&D expenditure divided by sales ($RD/Sales \times 100$ and $NETRD/Sales \times 100$) These two variable allow us, to test different hypotheses:

- H_1 : Full crowding–out
  The use of RD allows us, to test for full crowding–out. Suppose "the average firm" decided on its R&D budget for the business year and it is set to 100 currency units (CU). However, the firm gets aware of public funding opportunities, files an application, and receives a subsidy of 20 CU for an additional R&D project. Full crowding–out would imply that the firm still spends 100 CU on R&D including the subsidy. If we find a significant treatment effect in the variable RD, we can thus reject the hypothesis of full crowding–out, on average.

- H_2 : Partial crowding–out
  Similarly we can test for partial crowding–out using $NETRD$. Again suppose the average firm received a subsidy of 20 CU, and we actually observe 100 CU of $NETRD$. If the treatment effect in $NETRD$ is

level unless stated otherwise.

not negative, we do not have to reject the null hypothesis of no partial crowding–out.

- H_3 : Acceleration effect
  Finally, if we find that the average treatment effect on the treated in $NETRD$ is significantly positive, we can reject the hypothesis of no accelerating effect of the subsidies, because the average firm spends more than the amount of subsidies received in case of treatment than in the absence of a treatment.

In the second stage, we disentangle RD into the counterfactual situation RD^C and the additionally induced R&D, α^{TT} (the subsidy and the accelerated private investment). The endogenous variables in this stage are the number of patent applications $PATENT$ and a dummy variable indicating firms that filed at least one patent, $D(PATENT > 0)$. This forms our fourth hypothesis on technological progress or performance:

- H_4: The additional technological progress induced by public incentives
  In case of the support of an acceleration effect (H_3) it may indeed be possible that subsidies increase the technological performance in Germany. To test this hypothesis, we consider a “patent production function” and investigate whether a possibly positive treatment effect, that has been estimated before, contributes positively and significantly to patent applications of firms. If we find this effect, we do not have to reject the presumptions of the European Action Plan 2010, namely that policy incentive schemes can actively increase Europe’s technological performance.

The further factors in Table 2 are treated as exogenous regressors: The log of the number of employees in thousands, ($\ln(EMP)$), controls for size effects. The dummy variable $EAST$ indicates firms that are located in Eastern Germany. Due to the German reunification in 1990, Eastern Germany is still in transition from a planned economy to a market economy, and the firm behavior may be different. For instance, most firms were newly founded since the reunification and they are on average smaller than Western German firms. Moreover, Eastern German firms are preferred in the policy incentive schemes, and special schemes have been launched exclusively for such in order to accelerate the catching–up process in this region. The log of firm age ($\ln(AGE)$) controls for additional maturity effects. On one hand, younger firms may be more likely to receive subsidies, because in Germany exist special start–up programs. On the other hand, older companies may be more experienced in R&D and applying for subsidies, ceteris paribus. A very important variable in the estimation of the propensity score of the subsidy receipt is the patent stock (PS). The patent stock is generated from a series of patent applications (timed by application date) since 1980 for every firm and approximates the past R&D activities of a firm. Previous successful R&D is assumed to positively influence the probability of receiving subsidies. The stock of patents is generated by the perpetual inventory method as

$$PS_{it} = (1 - \delta)PS_{i,t-1} + PA_t$$

where PA denotes the number of patent applications by firm i in year t and δ is the constant depreciation rate of knowledge which is set to $\delta = 0.15$ as common in the literature (see, for example, Hall, 1990, or Griliches and Mairesse, 1984, who have shown that the magnitude of the assumed rate of obsolescence had almost no effect in the estimation of the relationship between productivity and the R&D capital stock). The patent stock enters the regression as PS/EMP in order to reduce collinearity with firm size. Moreover, we use the lagged patent stock of $t - 2$ to avoid endogeneity with current $R\&D$.

The dummy $GROUP$ indicates firms that belong to a group and $FOREIGN$ is a subset of $GROUP$ referring to companies belonging to a group with a foreign parent company. This variables control for different governance structures. Firms that belong to a group may be more likely to receive subsidies because they presumably have better access to information about governmental actions due to their network linkages. In contrast, if firms belong to a group with a foreign parent company, it may be the case that the group tends to file applications in its home country or that, due to the foreign ownership, a German subsidiary does not qualify for the federal technology programs.

We also control for competition. The export quota ($EXPORT$ = exports/sales) measures the degree of international competition a firm faces. Firms that engage in foreign markets may be more innovative than others and, hence, are more likely to apply for subsidies. $IMPORT$ denotes the import intensity (= imports/(imports plus domestic production)) and is measured at the 2–digit industry level. Furthermore, the Hirschmann–Herfindahl–Index (HHI) represents the domestic sellers concentration on the 3–digit industry level. These variables capture differences in competition among industries. Note that we use lagged values to avoid simultaneity problems.

A dummy variable for capital companies ($CAPCOM$) indicates for firms with liability limiting legal form.[9] Firms with such legal forms are registered in the German trade register. This may have an influence on the funding probability as firms are required to prove that they are business active at the time of application. Being included in the trade register serves as such evidence. Other firms like joint partnerships have to fulfill this requirement differently. As the authorities may be risk averse, they possibly tend to prefer registered companies for funding. Finally, twelve industry dummies control for non–observed differences among industries as well as six time dummies capture changes in the macroeconomic environment.

Comparing the samples of publicly funded and non–funded firms before the matching as presented in Table 2 shows that there exist significant mean differences in all variables used. This points to the fact that the recipients of subsidies are a selective sample. For example, the funded firms are larger, have a higher patent stock per employee, and also achieve higher export quotas, on average. In addition, they spend significantly more on R&D than non–funded firms. However, the research question followed in the upcoming matching process is whether these differences in R&D spending can be assigned to the receipt of subsidies.

5 Empirical Results

5.1 The funding probability

We start with the estimation of the propensity score $P(x_i'\beta)$ which is subsequently used in the matching algorithm to obtain the average treatment effect on the treated, α. Table 3 shows the estimation results of the probit model on the receipt of subsidies. The marginal effects are calculated at the sample means, and their standard errors are obtained by the delta method.

Large firms are more likely to be considered in the federal technology programs. They conduct presumably more R&D projects than smaller firms and are able to apply for public $R\&D$ support with several proposals. Better

[9] It corresponds to the German legal forms: GmbH, GmbH&Co.KG, and AG.

Table 3: Probit estimation on the receipt of public R&D funding

variables	coefficient	std. err.	marg. effects[a]	std.err.
PS/EMP (lagged)	3.09***	0.58	0.70***	0.10
ln(EMP)	0.32***	0.03	0.06***	0.00
$EAST$	1.23***	0.14	0.33***	0.05
ln(AGE)	0.10***	0.03	0.02***	0.01
$GROUP$	0.11	0.13	0.02	0.03
$FOREIGN$	-0.19	0.18	-0.02	0.03
$CAPCOM$	0.02	0.15	0.00	0.03
$EXPORT$	0.25*	0.13	0.04*	0.02
$IMPORT$ (lagged)	0.17	0.32	0.03	0.06
HHI (lagged)	-0.29	0.44	-0.05	0.08
Constant term	-4.33***	0.30		
	Tests on joint significance			
Industry dummies	$\chi^2(12) = 148.14$ ***			
Time dummies	$\chi^2(6) = 46.75$ ***			
# of obs.	3,779			
Log Likelihood	-1,297.72			
McFadden R^2	0.2056			

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

a) Marginal effects are calculated at the sample means.

developed structures of information and organization may contribute as well to the higher propensity and large firms may have advantages in answering the bureaucratic demands of the application process. Firms' age also has a positive impact on the probability to receive a subsidy. Therefore, we conclude that the experience argument and also a firm's track record outweighs the existence of special start–up programs, on average. Firms that have been innovative in the past, as measured by the lagged patent stock per employee, achieve a higher probability to receive public support than other firms. This result reflects possibly the strongest selection criterion by the Federal Government besides the review of the submitted proposals. Public authorities seek to maximize the expected social return of the subsidies. Thus, applicants showing previous successful R&D projects are preferred over other firms, because it is expected that such firms maintain more knowledge capital and experience, so that the probability of a complete failure of the targeted research is very low.

As expected, the EAST dummy is significantly positive reflecting the larger supply of public incentive schemes in Eastern Germany in order to foster the catching–up process. $EXPORT$ is the only competition measure which is, at least weakly, significant in the regression. Firms that face higher international competition are, on one hand, possibly more relying on innovative products, and are therefore more likely to apply for public grants. On the other hand, this may reflect the Federal Government's goal to strengthen Germany's international competitiveness. Furthermore, the industry dummies and the time dummies are both jointly significant at the 1% level. The variables controlling for different governance structures do not have any impact on the funding probability.

As we find highly significant industry differences, but also several insignificant variables, we decided to use some interaction terms of the significant variables and the industry dummies in order to achieve a better fit of the model and, thus, a better approximation of the conditional independence assumption needed for the upcoming matching procedure. In particular, we added interactions of the patent stock with $EAST$, firm size interacted with $EAST$, and interactions of all industry dummies with firm size. A likelihood ratio test of the model including these interaction terms and the model presented in Table 3 reveals that the additional regressors add to the fit: the LR–statistic amounts to 47.38 and is distributed $\chi^2(14)$. As the interaction terms are jointly significant at the 1% level, we use the extended model to predict the propensity score.

5.2 Estimation of the average treatment effect on the treated

In the second step, the impact of the public $R\&D$ project funding on firms R&D spending is estimated. Initially, we used only the propensity score as the matching argument, but it turned out that the matching quality is significantly improved when the firm size ($LN(EMP)$) is also included in the matching function. Recall that for a potential control observation to be picked as a nearest neighbor, it is also required to operate in the same industry as the corresponding treated firm (see Table 1). Given these requirements and our relatively large set of covariates, especially including the innovation history of firms measured by the patent stock, and the inclusion of several interaction terms to take industry specificities into account, we assume that the conditional independence assumption is fulfilled in our application of the matching methodology. Unfortunately, this assumption is not testable.

Imposing the common support only leads to a loss of 15 observation on subsidized firms for which no appropriate control observation is included in the sample of non–treated companies (see Step 1 in Table 1). As this amounts only to 2.6% of the subsidy recipients, the application of the matching methodology is justified with respect to the large common support among both groups, in our opinion.

Table 4: Results of the NN–matching[a]

	funded firms	non–funded firms		
# of observations:	$N^T = 573$	$N^C = 573$		
variables	mean	mean	mean diff.	std. err.[b]
PS (lagged)	0.02	0.02	0.00	0.00
$\ln(EMP)$	5.68	5.67	0.01	0.09
$EAST$	0.35	0.36	-0.01	0.04
$\ln(AGE)$	2.87	2.87	0.00	0.10
$GROUP$	0.32	0.32	0.00	0.03
$CAPCOM$	0.97	0.97	0.00	0.01
$FOREIGN$	0.04	0.03	0.01	0.01
$EXPORT$	0.32	0.31	0.01	0.02
$IMPORT$	0.31	0.30	0.01	0.02
HHI	0.06	0.07	-0.01	0.01
Propensity Score $P(x_i'\beta)$	0.32	0.32	0.00	
RD	4.11	2.96	1.15***	0.38
$RD/Sales \times 100$	6.26	4.37	1.89***	0.52
$NETRD$	3.86	2.96	0.90**	0.37
$NETRD/Sales \times 100$	5.34	4.37	0.97**	0.49
Matching results for SMEs (firms with 500 employees at most)				
# of observations:	$N^T = 234$	$N^C = 234$		
RD	1.24	0.75	0.49***	0.13
$RD/Sales \times 100$	10.22	6.14	4.08***	1.12
$NETRD$	1.08	0.75	0.33***	0.13
$NETRD/Sales \times 100$	8.29	6.14	2.15**	1.06

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

[a] The matching function includes the estimated propensity score and $\ln(EMP)$, and the selected controls are recorded in the same industry as the corresponding subsidized firm. The samples are also balanced with respect to time (6 time dummies not presented).

[b] Standard errors account for sampling with replacement (see Lechner, 2001).

For the remaining 573 observations in the group of treated firms, we find appropriate twins. As a first test whether the matching has been successful, we re–estimate the selection equation as presented in Table 3 including the interaction terms, but with the matched sample. We expect that a Likelihood Ratio test on joint significance of all coefficient should not reject the null hypothesis. The statistic is distributed $\chi^2(42)$ and amounts to $LR = 11.79$

which is insignificant, and we can conclude that the matching balanced the samples sufficiently well. As a further check, we also conduct t–tests on mean differences for all variables (including time dummies). As Table 4 reports there are no significant differences in the exogenous firm characteristics and in the estimated propensity score after the matching (see the upper part of Table 4).

Although there is no significant difference with respect to the exogenous characteristics between both groups, the R&D expenditure of the funded firms is significantly larger. This effect can be assigned to the public funding. Going back to our main hypotheses (see Section 3), we reject the first hypothesis (H_1) of full-crowding out effects, because we find a significant treatment effect on the treated with respect to RD at the 1% level: $\alpha^{TT}_{RD} = 4.11 - 2.96 = 1.15$. The effects for the R&D intensity are also significant at the 1% level. Furthermore, we test our hypotheses H_2 and H_3 jointly using $NETRD$: The average treatment effect on the treated is $\alpha^{TT}_{NETRD} = 3.86 - 2.96 = 0.90$ which is significant at the 5% level. This result also holds for the specification as Net–R&D intensity.

Consequently, we conclude that the subsidized firms do not only spend the volume of the subsidy additionally on R&D, but do also raise further private funds if they receive public support. In fact, we do not have to reject the assumed mechanism by the European Action Plan that recipient firms add new projects to their R&D portfolio when they receive a subsidy. While they receive a proportion of the total project cost as a grant (usually 30 to 50%), they increase their private investment, too. Note, however, that we can only state that there is some accelerator effect, but cannot tell whether the firms raise the additional share to be financed completely from new sources. It still might happen that the recipients increase the private investment not by the total remaining cost to be financed for the additional project, but only raise their net investment by a "significantly larger than zero" amount and make the rest of the necessary funds available by some reallocation of their R&D project portfolio. In summary, we conclude that the hypothesis of partial crowding–out can be rejected in our analysis and we can confirm that the R&D subsidies lead in fact to an acceleration effect in Germany. One argument might be that the subsidy remarkably reduces the economic risk of the targeted projects so that firms achieve a better position to raise external capital to finance R&D projects. Lerner (1999) pointed out that a grant in US SBIR program served as a quality certificate especially for small and medium–sized enterprises in order to acquire new bank loans. Such mechanism may be at work in Germany, too.

Motivated by this hypothesis, we re–estimated the probit model and the matching for a subsample of small and medium–sized firms only (firms with 500 employees at most). This subsample contains 2,168 observations, and the matched samples consist of 234 observations each. The different test statistics indicate that the matching is as successful as in the full sample's case. The results of the estimation are presented in the lower part of Table 4. Again, we can reject the crowding–out hypotheses. In the full sample, the "acceleration effect" (H_3) of public funding amounts to an increase on 30% of net–R&D investment ($\alpha^{TT}/NETRD^C = 0.90/2.96$). In the sample of SMEs, however, this effect is 44% ($\alpha^{TT}_{SME}/NETRD^C_{SME} = 0.33/0.75$). In fact, it turns out that the small firms increase their private investment well above the average when they are considered in public incentive schemes. As it is commonly agreed in the economic literature that smaller firms are more financially constrained than larger firms (see e.g. the survey on the financing of R&D by Hall, 2002), we find support for Lerner's statement that the governmental approval of a research proposal serves also as quality certificate for other external financiers.

5.3 The effect on technological progress

Since, we have shown that the federal subsidies indeed accelerate R&D spending in Germany, we now turn to the second major research question in this paper, that is, if the additionally induced R&D leads to technological progress as presumed by the European Action Plan 2010. We measure technological progress or performance as the patent activity at the firm level.

As dependent variables the number of patent applications per year ($PATENT$) and a dummy whether a firm filed at least one patent per year ($D(PATENT > 0)$) are chosen. Obviously, R&D spending is the most important input factor for the "patent production function". We use the results of the foregoing matching procedure to disentangle the different components of R&D investment in this stage: $\widehat{RD}^C$ represents the part of the total R&D expenditure that the firms would have invested anyway, that is, in absence of subsidies. Note that $\widehat{RD}^C$ is just equal to RD for the non–recipient firms. In addition, the treatment effect on the treated α^{TT} is the additionally induced R&D (the subsidy plus the additionally induced private

Table 5: Estimation of the patent outcome equations

	number of patent applications (negbin regression)		patent probability (probit model)	
	full sample	SME	full sample	SME
variables	coefficient (std. err.)$^+$	coefficient (std. err.)$^+$	coefficient (std. err.)$^+$	coefficient (std. err.)$^+$
$\widehat{RD}^C$	0.24***	0.63***	0.10***	0.26***
	(0.02)	(0.09)	(0.01)	(0.04)
α^{TT}	0.16***	0.39***	0.10***	0.26***
	(0.01)	(0.06)	(0.01)	(0.06)
$EAST$	-0.90***	-0.39**	-0.46***	-0.18***
	(0.12)	(0.15)	(0.07)	(0.08)
		Tests on joint significance		
Ind. dummies $\chi^2(12)$	157.52***	32.61***	160.09***	52.41***
Time dummies $\chi^2(6)$	14.62**	15.47**	6.79	12.61**
# obs.	3,764	2,168	3,764	2,168
Log Likelihood	-4,641.48	-1,446.02	-1,971.71	-869.57
McFadden R^2	0.0680	0.0436	0.1326	0.0831

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

$^+$ standard errors are bootstrapped.

research investment). For the non–subsidized firms this variable takes the value zero by construction. In addition to these two variables, we control for industry differences in patenting behavior by using the twelve industry dummies, and also include the six time dummies controlling for intertemporal changes in patenting behavior. The dummy variable $EAST$ accounts for a possibly lower average patenting activity of the still developing Eastern German economy. We present bootstrapped standard errors as the R&D measures are estimated figures (for the treated firms) and thus ordinary standard errors would be biased downward. We used 200 replications of the procedure to estimate the bootstrap standard errors.

The results of negative binomial regressions for the patent counts and of probit models for the patent dummy are presented in Table 5. Note that for the negative binomial model, we tested for overdispersion in both samples and the LR statistics reveal that a poisson model is rejected in both cases. The R&D expenditure in the counterfactual situation $\widehat{RD}^C$ and the treatment effect exhibit a statistically significant and positive impact on both the patenting decision and the number of patent applications. Only in the case of the count data model, tests yield that the hypothesis of equal coefficients of $\widehat{RD}^C$ and α^{TT} is rejected ($\chi^2(1) = 16.56[32.61]$ in the full [SME]

Table 6: Estimation of the patent outcome equations: marginal effects

	number of patent applications (negbin regression)		patent probability (probit model)	
variables	full sample	SME	full sample	SME
$\widehat{RD}^C$	0.20***	0.18***	0.03***	0.06***
α^{TT}	0.14***	0.11***	0.03***	0.06***
$EAST$	-0.59***	-0.10**	-0.14***	-0.04***

sample). Further results are a significant lower patent activity for Eastern Germany, and the industry and time dummies are jointly significant in most regressions (except the six time dummies in the probit regression using the full sample). The lower patenting activity in Eastern Germany might have several reasons: first, a more on imitation based R&D strategy that is focused on catching–up with Western Germany and other countries, or second, a lack of knowledge with respect to the patent system and related organizational issues, or third, just smaller average firm size. As a further robustness test, we re–estimated the model including the log of firm age, firm size (measured by six size dummies instead of a continuous variable in order to reduce multi–collinearity with R&D spending and firm age) and the export quota. Firm size and age are included to control for the experience and general propensity to use patents for the protection of intellectual property, and exports control for the different competitiveness of firms which perhaps is reflected in the originality of their research. We find that the larger the firms, or the older the firms and the more export–oriented the firms are, the more patents they file (not presented in detail). The coefficients of the R&D variables change only marginally (downwards) and the interpretation with respect to R&D and technology policy is the same. Note that the $EAST$ dummy remains significant in all regressions. Thus the patenting gap between Western and Eastern Germany cannot be easily explained by conventional measures like firm size and age. A more detailed investigation on the determinants explaining this gap is beyond the scope of this paper and remains for further research.

Table 6 presents the marginal effects at the mean of the explanatory variables. As the results show, the marginal effects of the R&D terms are always significant. On average, the marginal effect in the count data model is 0.2 for the purely privately financed R&D and 0.14 for the additionally induced R&D stimulated by subsidies. The effect of the private R&D expenditure is thus slightly higher than that of the publicly induced R&D expenditure. This holds also true for the sample of SMEs, but the effects on patents are somewhat smaller, on average. In the probit model, however, the reverse is the case: the marginal effects to file at least one patent are larger for the smaller companies (conditional on a lower average patent propensity, of course). In both samples there is no differences between the two R&D components. It seems that the public incentive schemes are a good instrument to get firms to patent. They are as efficient as purely privately financed R&D. Again, this points to the hypothesis of financial constraints. For instance, companies that show a good track record of successful research are possibly able to finance their activities by both internal and external capital. A considerable proportion of other firms, however, might have good project proposals, but they are not able to raise external capital on the market. The receipt of subsidies reduces the financial constraints and firms are able to conduct the desired research projects which in the end even qualify for patents. This is also emphasized by the larger marginal effects in the probit regression using the SME subsample. In conclusion, we find that both the purely privately financed R&D ($\widehat{RD}^{C}$) as well as the additionally stimulated R&D spending or exhibit a positive impact on patenting activity. Hence, the main results of our study is that public policy schemes lead indeed to an increased technological performance in the economy.

6 Conclusions

The "European Action Plan 2010" aims at strengthening the technological performance and thus the international competitiveness to secure long–term employment in European member states. Therefore, the 2002 EU member states agreed on the idea to raise the European R&D expenditure from currently 1.9% of GDP to 3.0% by 2010 in the European Community. In order to achieve this goal, national governments are requested to reinforce their national technology programs to support research and development in the business sector.

In line with that task, this paper analyzes the effects of public R&D project funding on R&D expenditure and subsequently the effect of the publicly induced R&D spending on the patenting behavior of German firms. Conducting a treatment effects analysis to study the crowding–out versus the complementarity hypothesis yields that we can reject full as well as partial crowding–out effects, on average. In fact, public incentive schemes seem to accelerate the R&D spending in the business sector. In a second step, we implement the results of the treatment effects analysis into a simple patent production function, where R&D investment is disentangled into two components: on one hand, the purely privately financed part of the total R&D budget that firms would have spend in the absence of subsidies and, on the other hand, the additionally induced R&D expenditure that is stimulated by the subsidy (the sum of the subsidy itself and the additionally spent private funds due to the receipt of subsidies). We find that both the purely financed R&D and the estimated treatment effect show a positive impact on the patenting behavior of firms. Hence, we do not have to reject the presumed mechanism behind the European Action Plan. Public policy initiatives indeed foster the private R&D engagement, so that the meeting of the Action Plan's 3% goal can actually be promoted by public policy. Furthermore, it contributes to the ultimate goal of the Action Plan, namely to increase Europe's technological performance, as the regression analysis reveals that even the publicly stimulated additional R&D leads to an increased patenting activity.

Of course, our study has a number of caveats that remain for further research. First, we only consider Germany as an example of a European economy. It is questionable whether our results hold for other countries within the European community. Second, patents are a measure of technological performance. While patent indicators are a broadly accepted concept to measure technological development, it is a narrow measure of innovative activity, though. More general indicators, like successful innovations in terms of sales with new products or cost reductions could serve as further indicators of innovation outcome. Also employment growth as the ultimate goal of the Action Plan would be a very interesting extension of our study. However, we chose patents due to the cross–sectional nature of our data, as they should be the closest outcome indicator to the actual research projects with respect to timing. Although our analysis would also benefit from the availability of panel data to control for individual fixed effects, it is a necessary precondition for analyzes targeting the broader measures of innovation outcome or employment as the ultimate success factor. In those cases, one had to allow for longer lags between the research and perceptible effects on the product or labor market.

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