FACULTY OF LAW, ECONOMICS AND FINANCE

CREA Discussion Paper 2017-12

Management

Center for Research in Economics and Management
University of Luxembourg

Input and Output Additionality of R&D Subsidies

available online : http://wwwfr.uni.lu/recherche/fdef/crea/publications2/discussion_papers

Dirk Czarnitzki, KU Leuven, Belgium
Katrin Hussinger, CREA, Université du Luxembourg

July, 2017

For editorial correspondence, please contact: crea@uni.lu
University of Luxembourg
Faculty of Law, Economics and Finance
162A, avenue de la Faïencerie
L-1511 Luxembourg

UNIVERSITÉ DU LUXEMBOURG

Input and Output Additionality of R&D Subsidies[1]

This paper is forthcoming in *Applied Economics*

This version: July 2017

Abstract

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

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

Contact:

Dirk Czarnitzki, K.U.Leuven, Dept. of Managerial Economics, Strategy and Innovation, Naamsestraat 69, 3000 Leuven, Belgium

E-Mail: dirk.czarnitzki@econ.kuleuven.be; Phone: +32 (0) 16 326 906

Katrin Hussinger, University of Luxembourg, Faculty of Law, Economics and Finance, 162 A, Avenue de la Faïencerie, L-1511 Luxembourg

E-Mail: katrin.hussinger@uni.lu; Phone: +352 46 66 44 6404

[1] This research was part of the project "Einsatzmöglichkeiten neuer quantitativer Ansätze zur Wirkungsanalyse öffentlicher Forschungsförderung" financed by the German Federal Ministry for Education and Research (BMBF). The authors are grateful to the BMBF for providing the PROFI database on public R&D project funding and to Creditreform for the access to their firm database. Moreover, we thank the participants of following conferences: "The Economics and Management of Science and Technology", KU Leuven, May 2004; 10th International Schumpeter Conference, Milan, June 2004; EARIE 2006, Amsterdam, The Netherlands. Finally, we are indebted to Spyros Arvanitis, Guido W. Imbens and Pierre Mohnen for helpful comments. The paper was partly written during a research stay of Dirk Czarnitzki at the University of California, Berkeley. The hospitality of the UCB is gratefully acknowledged.

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 was in excess of EUR 200 billion per year in 2009 (OECD, 2012) and has been widening fast, with potentially alarming consequences for long-run technological performance, growth and employment. For this reason, the EU member states agreed on several initiatives to bridge this growing gap. Prominent examples are the so-called Barcelona and Lisbon objectives and the Agenda 2020. The major objective is to increase the average gross expenditure on research and development (GERD) to 3.0%, of which two thirds should be funded by the private sector. While for some European economies like Finland, the threshold values are already passed, Germany's GERD as percentage of GDP was at 2.5% in 2001 and increased to 2.8% in 2010. The EU-27 average was at 2.0% in 2010.[2]

In order to reach policy goals like the 3% goal, European countries employ national initiatives to foster private R&D spending (see e.g. European Commission, 2003). The presumed mechanism is that public incentives increase R&D engagement in the business sector and that such additional publicly induced R&D activities lead to new products and processes improving Europe's technological performance. It is by no means granted that these presumed mechanisms work: First, every firm has an incentive to apply for subsidies and could substitute public funding for private research investment. If full crowding out occurs, public incentives would not lead to

[2] Data on GERD over GDP is taken from Eurostat: http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=1&language=en&pcode=t2020_20.

any improvement of technological performance. Second, it is a priori 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 that promise the highest expected returns. Hence, publicly funded R&D projects would 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 whether the mechanisms behind public subsidy initiatives work at the firm level: the link between public funding and R&D input, in the first step, and the relationship between additionally induced R&D input and technological performance in second step. Technological performance is measured by patent applications and citation-weighted patent applications. The latter measure takes the quality R&D outcome into account. The essential contribution to the literature is that we explicitly take into account the effect of additionally induced R&D due to public incentive schemes on the firms' patent productivity and quality. Beforehand, researchers either analyzed the input side or the output side of the innovation process. In this study, in contrast, the direct impact of subsidies on innovation input and the indirect effect of subsidies on innovation output through possibly increased R&D spending are modeled 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 an improvement of Europe's technological performance by current technology policy.

The remainder of the paper is organized as follows: The next section describes and motivates the setup of our empirical model. Section 3 reviews recent studies on the evaluation of different

R&D subsidy programs and 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 Public Subsidies in Germany

Our empirical test focuses on the direct R&D subsidy program in Germany in the period 1992-2000. Since the 1950s, the German Federal Government fosters R&D activities in the private sector to accelerate technological progress and to enhance national competitiveness and long-term growth. In 1999, for instance, about EUR 2 billion were spent to support civilian R&D projects in Germany. About EUR 0.54 billion reached the business sector through direct funding of R&D projects granted by the Federal Ministry of Education and Research (BMBF) (BMBF, 2000). As compared to 1998, the BMBF's R&D expenditure increased by 3.5% in 1999. Also in the following years, a steady increase was observed (Czarnitzki et al., 2004). Table 1 shows that the amounts invested in the direct project subsidy program increased over time. An upwards trend is also observed for the average amount of funding per funded R&D project. As a result of these large amounts, the effects of public R&D subsidies are of high political interest. Note that there are no R&D tax grants in Germany turning the direct project subsidies into the most important funding instrument.

Figure 1 about here

With respect to the funding procedure, companies have to apply with a specific project proposal. The official application form requires detailed information on the company and its planned R&D projects. There is a peer review process after which grants are given as "matching grants" to the selected projects, which means that applicants have to contribute at least 50% to the subsidized projects. The government sponsors at most 50% as is prescribed in the funding guidelines of the European Commission (1996) and in German regulations (BMBF and BMWi, 2001). Over the 1990s, the subsidy program developed a preference for “new” technologies, such as biotechnology, microsystems and chemical technologies, and projects with broad and fast industrial application potential which increased the number of small and medium sized firms among the subsidy recipients. The increase of small and medium sized subsidy recipients is also driven by the reunification of Western and Eastern German in 1990 (Czarnitzki et al., 2003).

3 Model Setup

There are clear economic rationales for 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 by the innovator (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 innovation in the economy is below the socially desirable level. This economic rational is the main reason for governments to subsidize private R&D projects. Public funding reduces the price for private investors and thus the otherwise too expensive innovation projects are carried out. However, a firm has always an incentive to apply for public R&D support, even if the expected private return is positive and if the R&D projects could be conducted using the own financial means. If public support is granted, the firm 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 R&D support. The crowding out versus incentive hypothesis is the first mechanism to be investigated. Only if full crowding out effects can be rejected, total R&D activity is increased by governmental incentive schemes.

There are also clear rationales suggesting that public subsidies induce additional R&D investments by the subsidized firms. First, most subsidy programs are defined in such a way that they demand additional R&D investments by the funded firm. As explained in the previous section, regarding the direct project R&D subsidies in Germany, the funding authorities subsidize at most 50% of the total project costs. Subsidized firms have to finance the remaining 50% with their own means. Hence, if the subsidy program works as expected it should induce additional private R&D investment that would not have taken place in the absence of R&D support. Second, there is an economic rationale suggesting that subsidies induce additional R&D investment by the private sector. David et al. (2000) provide a simple economic framework to illustrate this. Assume that a firm has a pool of potential R&D projects that it can decide to invest in or not. The firm would then rationally evaluate these projects according to the expected costs and benefits in order to calculate their expected rate of return. The potential projects can be ranked in descending order of expected return, thereby forming its marginal rate of return (MRR) curve. The MRR schedule then decreases with each additional project. Now, consider an upwards-sloping marginal cost of capital (MCC) curve that depicts the opportunity costs of investment into an additional R&D project. Under the assumption of profit maximization, the optimal level of R&D investment is determined by the intersection of MCC and MRR. In this scenario, public subsidies would shift the MCC curve to the right. This would permit the firm to undertake additional R&D projects with their own money, all other things being equal.

After having investigated whether subsidies induce additional private R&D investment rather than leading to a crowding out of private investments, we analyze whether the additional R&D

induced by public policy leads to benefits in terms of technological performance. If firms maximize profit, we can assume that they 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. 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 project 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 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 to make sure that R&D subsidies indeed lead to more innovation.

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.[3] This can be expressed by the average treatment effect on the treated

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

[3] We focus on the average treatment effect on the treated since only a selective part of the population of all firms participates in the R&D subsidy program. This measure is informative for the policy maker as it shows whether the subsidy is beneficial for the average funded firm. It, hence, answers the question whether the R&D subsidy program stimulates private R&D among the funded firms or whether a crowding out effect occurs.

where $R\&D_i^T$ indicates the R&D expenditure in case of treatment, $R\&D_i^C$ 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 in the academic and policy domain (see Griliches, 1990, or OECD, 1994). We focus on patents and citation-weighted patents as R&D outcome. The citation-weighted patent outcome takes patent quality into account (Trajtenberg, 1990, Hall et al., 2005). Citation-weighted patent measures have for instance been used by Bloom and Van Reenen (2002) and Aghion et al. (2005). It might appear that firms patent more if they receive public subsidies in order to signal successful project completion to the funding agency, but that these patents have a lower quality.

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 we 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

$$PATENT_i = f(R\&D_i^C, \alpha_i, other\ firm\ charactertistics) \quad (2)$$

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.

4 Literature Review and Estimation Strategy

4.1 Evaluations of R&D subsidy programs

Since innovation is important for economic growth and national competitiveness, many governments spend significant time and money into public initiatives to foster private innovation activities. The success of policy measures is ex ante unclear and typically only ex post analyses of the benefits of such programs are possible. Ex-post evaluation studies exist for different R&D subsidy programs in various countries. 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 up to 2000. They conclude that the majority of the studies considered find a complementary relationship of privately and publicly financed R&D. One major criticism of both surveys is the disregard of a possible selection bias in the early evaluations of R&D subsidy programs. If, for example, the government follows a "picking the winner" strategy, it will subsidize those firms that are most innovative. A comparison of the R&D expenditure of subsidized and non-subsidized firms would then be biased in favor of the subsidized firms. The evaluation literature since 2000, as surveyed by Cerulli (2010), takes selection of firms into public R&D programs into account. Zuniga-

Vincente et al. (2014) provide the most recent and most extensive literature survey on the effect of public subsidies on R&D investment.

Evaluation studies exist for public subsidy programs in a variety of countries[4] and employ different econometric approaches to control for selectivity of firms into subsidy programs.[5] Most of these studies conclude that there is a positive treatment effect on the treated as measured in terms of additional R&D inputs (Zuniga-Vincente et al., 2014).[6]

While most of the evaluation studies focus on input additionalities, only a few studies focus on the effect of R&D subsidies on R&D output. Branstetter and Sakakibara (1998, 2002) study the performance of Japanese research consortia which are heavily subsidized. They 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 U.S. In order to do that they, for example, regress patents on R&D input and the consortium dummy. Branstetter and Sakakibara (1998) find a positively significant coefficient for 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 (see also Fornahl et al., 2011, for collaboration

[4] E.g. for Finland (Czarnitzki et al., 2007, Takalo et al. 2008), Flanders (Aerts and Czarnitzki, 2005, Aerts and Schmitt, 2008), France (Duguet, 2004), Germany (Czarnitzki and Fier, 2002, Almus and Czarnitzki, 2003, Hussinger, 2008), Israel (Lach, 2002), Italy (Cerulli and Poti, 2010), Canada (Berube and Mohnen, 2009), Luxemburg (Czarnitzki and Lopes Bento, 2010), Spain (Busom, 2000, Gonzales et al., 2005, Gonzales and Pazo, 2008, Gelabert et al., 2008), the ATM (advanced manufacturing technologies) program in Switzerland (Arvanitis et al., 2002), the U.S. SBIR program (Wallsten, 2000) and the U.S. chemical industry (Finger, 2008), South Africa (Czarnitzki and Lopes Bento, 2010) and Latin America (Hall and Maffioli, 2008). Most of these studies can rule out a full crowding out effect.

[5] Prominent methods are matching estimators (e.g. Czarnitzki and Fier, 2002, Almus and Czarnitzki, 2003, Czarnitzki et al., 2007, for heterogeneous treatments), instrumental variables methods (e.g. Wallsten, 2000) and selection models (e.g. Busom, 2000, Hussinger, 2008, for semiparametric versions).Gonzales et al. (2005) and Takalo et al. (2008) develop structural models to access the effect of subsidies in the subsidized firms.

[6] Exceptions are Busom (2000) who finds a partial crowding out effect for Spain and Wallsten (2000) who reports a substitutive effect of subsidies for the U.S. SBIR program. Gelabert et al. (2008) find differences in the effectiveness of public subsidies depending on the level of appropriation in the firm’s industry.

networks of German biotech firms, and Czarnitzki et al., 2007 for collaborative German and Finnish firms).

Berube and Mohnen (2009) investigate the effect of R&D subsidies (on top of R&D tax reductions) for Canadian firms. They find that firms which receive a subsidy in addition to the tax benefit are more likely to introduce new products to their province, Canada, North America and the world than the control group. In addition, the revenue from new products is higher for subsidized than for non-subsidized firms. Less positive evidence is found by Svensson (2013) who shows that patents that are generated by soft publicly sponsored R&D are less likely to be prolonged than patents taken out of privately financed R&D or than patents receiving market-oriented public loans.

The setup of our model is different from the studies referred to above since we explicitly take into account that the subsidy affects primarily R&D input and reveals the benefit only in the second step from additional R&D input to R&D output. We contribute to the subsidy literature by suggesting an approach for accessing the productivity of the additional R&D input induced by public grants.[7]

4.2 Estimation strategy to assess the crowding out hypothesis

As mentioned above, advanced econometric evaluation techniques have been developed to identify treatment effects when the available observations on individuals or firms are subject to a selection bias. A selection bias typically occurs when participants in public measures differ from non-participants in important characteristics. The literature on the econometrics of evaluation offers different estimation strategies to correct for a potential selection bias (see Heckman et al., 1997, Heckman et al., 1999, for surveys) including the difference-in-difference estimator, control

[7] The here suggested approach has applied by the later literature in the meantime, e.g. Hussinger (2008).

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 pooled cross sections, we cannot apply this estimator. Therefore, we choose the matching estimator. The main advantage of the matching method over IV and selection models is that we neither have to assume a 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 controls for observed heterogeneity among treated and untreated firms only. As we discuss in the next section, we believe that our set of covariates allows us to assume that selection on unobservable effects is unlikely. We show robustness of our results if IV estimations are used.

As clarified above, we estimate the average treatment effect on the treated as shown (see eq. (1)).[8] 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*:

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

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

[8] 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 and first application of the matching estimator in the context of R&D subsidies can be found in Almus and Czarnitzki (2003).

dimensionality" is based on Rosenbaum and 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, i.e. that 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}.

Table 1 about here

4.3 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 commercial success of the innovative product.

In empirical studies, patents are typically modeled 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. They further conclude that the contribution of the observed R&D history to the contemporaneous patent applications is rather 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 accounting also strategic aspects. Further, 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.[9]

Building on the results of Pakes and Griliches (1984) as well as on Hall et al. (1986), we use a cross-sectional approach with the contemporaneous R&D expenditure accounting also for the firms' 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. Another example of a cross-sectional analysis of the relationship between patents and R&D is provided by Jaffe (1986). The most common approach for estimating patent production functions are count data models. In this paper, poisson regression models are chosen to analyze the impact of the two R&D components on the number of patent application. We use the number of patent applications as well as the citation-weighted patent outcome of the firms as dependent variables. Since, the patent history of each firm is known to us, we use pre-sample mean poisson estimators (Blundell et al., 1995) in addition to pooled cross-sectional poisson models in order to control for firm-specific effects.

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

5 Data and Empirical Considerations

5.1 Data

Our final database results from linking different sources at the firm level. Company information is taken from the Mannheim Innovation Panel (MIP),[10] 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. Unfortunately many firms are only observed once in the survey, because participation is not mandatory and many firms are reluctant to publish information about innovation voluntarily. Since in our final sample more than 50% of the companies are only observed once, we conduct pooled cross-sectional analyses.

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. Linking the PROFI database and the patent database to the MIP required a text field search by firm names and addresses. Each potential match suggested by the algorithm was manually checked. The project level data was aggregated to the firm level. Patent data are taken from the German Patent and Trade Mark Office (GPTO). It contains information on all patent applications in Germany since 1979. Patent and firm data were linked using a computer-supported text search algorithm. Again, potential matches were checked manually. Patent citations were extracted from the PATSTAT patent database. Finally, information like firm age, legal status and major shareholding are taken from the database of Creditreform, the largest German credit rating agency. Some industry data is taken from the OECD STAN database and from the annual reports from the German antitrust commission. Our final sample is a firm-year level database.

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

The combination of the MIP and the PROFI database allows us to identify different categories of firms regarding their funding status: 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 Laender or the European Union (as reported in the survey) and, third, companies that did not receive any public R&D grants. Since we are interested in the public funding by the Federal Government, we drop the second group of firms. In consequence, 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 lead 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. It would not be sensible to construct a control group for such firms. 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 3,774 firm-year observations of which 586 refer to recipients of public R&D funding by the German Federal Government.

5.2 Variables

Dependent 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* includes the private investment as well as the subsidies. *NETRD* is equal to RD net the amount of subsidies.[11] As a robustness check of our results, we 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 variables allow us, to test different hypotheses:

[11] For convenience we omit the subscript *it* in the following. All variables are at the firm level unless stated otherwise.

- H1: 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.

- H2: 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 not negative, we do not have to reject the null hypothesis of no partial crowding–out.

- H3: 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 dependent variables in this stage are the number of patent applications *PAT* and the citation-weighted patent applications (*CIT*) as a measure for patent quality.[12] Patent citations are a commonly used measure for patent quality (Trajtenberg, 1990, Albert et al., 1991, Harhoff et al, 1999, Hall et al., 2005). This forms our fourth hypothesis on technological progress or performance:

- H4: <u>The additional technological progress induced by public incentives</u>

  In case of the support of an acceleration effect (H3) subsidies may indeed increase technological performance. To test this hypothesis, we consider a "patent production function" and investigate whether a possibly positive treatment effect that has been estimated before, i.e. the additional input due to the subsidy, contributes positively to patent applications of firms. If we find this effect, we do not have to reject the presumptions that policy incentive schemes can actively increase Europe's technological performance. If we find the effect for citation-weighted patents as well we can conclude that patents are not taken out for strategic reasons, e.g. to signal a positive outcome of the funded project to the funding agency.

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

[12] The citations-weighted patent outcome is measured as the sum of the patents per year multiplied with the citations they receive in a five-year window after application.

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 regard to 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 variable controls 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 seller 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.[13] 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 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 account for non–observed differences among industries and 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 subsample of the firm population. 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

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

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. Table 2 presents the descriptive statistics.

Table 2 about here

6 Empirical Results

6.1 The funding probability

We start with the estimation of the propensity score $P(X'\beta)$ 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.

The results show several interesting findings. Large firms are more likely to be considered in the federal technology programs. Large firms conduct presumably more R&D projects than smaller firms and are able to apply for public R&D support with several proposals. Better 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 outweigh 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. Industry and time dummies are highly significant as LR-tests at the bottom of Table 3 show.

Table 3 about here

6.2 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 Figure 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 common support only leads to a loss of 15 observations of subsidized firms for which no appropriate control observation was found in the subsample 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.

For the remaining 571 observations in the group of treated firms, we find appropriate twin observations. In order to test whether the matching has been successful we conduct t–tests on mean differences for all variables (including industry and time dummies) after the matching. 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 (H1) of full-crowding out effects, because we find a significant treatment effect on the treated with respect to *RD* at the 1% level: $\alpha_{RD}^{TT} = 4.07 - 2.97 = 1.10$. The effects for the R&D intensity are also significant at the 1% level. Furthermore, we test our hypotheses H2 and H3 jointly using *NETRD*: The average treatment effect on the treated is $\alpha_{NETRD}^{TT} = 3.84 - 2.97 = 0.87$ which is significant at the 5% level. This result also holds for net R&D intensity.

Table 4 about here

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 subsidy policies 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.

6.3 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. We measure technological progress or performance as the patent activity at the firm level. As dependent variables the number of patent applications per year (*PAT*) and the citation-weighted number of patent applications (*CIT*) 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 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 inter-temporal 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 poisson regressions for the patent counts and citation-weighted patent counts are presented in Table 5. We use pooled cross-sectional poisson regressions and pre-sample mean regressions. The latter control for a firm-specific effect using the pre-sample mean of the dependent variable as an additional regressor (Blundell et al., 1995, Lach and Schankerman, 2008, Aghion et al., 2011). The R&D expenditure in the counterfactual situation $\widehat{RD}^C$ and the treatment effect exhibit a statistically significant and positive impact on the number of patent applications and its citation-weighted counterpart. Tests yield that the hypothesis of equal coefficients of $\widehat{RD}^C$ and α^{TT} can be rejected if a firm-specific effect is not controlled for, while publicly sponsored R&D is marginally less productive in the regressions that include a firm-specific effect. Private R&D increases patent outcome by 8.5% and citation-weighted patent outcome by 11.0%, while publicly induced R&D increases the patent outcome by 6.6% and citation-weighted patent outcome by 9.0% according to the pre-sample mean models.

Further, the results show a significantly lower patent activity for Eastern Germany, and the industry and time dummies are jointly significant. 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.

Table 5 about here

In order to show robustness of the results if selection on unobservables is taken into account we use IV estimations to test for the effect of subsidies on R&D investment and investigate the IV estimation-based effect of publicly induced R&D on innovation outcome. The results are shown in Tables 6 and 7 and discussed in the Appendix. Most important is that there is no significant difference between the productivity of private and publicly induced R&D in the patent equations and that the coefficients are remarkably similar when IV regressions are used in the first stage rather than a matching approach.

It seems that the public incentive schemes are a good instrument to get firms to patent. They are as efficient as (or marginally less efficient than) purely privately financed R&D. This points to the existence of financial constraints. 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. 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 result of our study is that public policy schemes lead not only to additional R&D investment, but indeed lead to increased technological performance in the economy.

7 Conclusions

Policy initiatives aim at strengthening the technological performance and thus the international competitiveness to secure long–term employment by granting innovation subsidies to the private sector. 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 effect 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 publicly induced R&D spending show a positive impact on the patent outcome and patent quality. Hence, we do not have to reject the presumed mechanism behind policy initiatives, 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. 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 many policy initiatives 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. Finally, it would be great to also have information about rejected grant applications to further improve our analysis. We share with the vast majority of previous studies on R&D subsidies that this information is not available (Cerulli, 2010, Zuniga-Vincente et al., 2014).

References

Aerts, K. and D. Czarnitzki (2004), Using Innovation Survey Data to Evaluate R&D Policy: The Case of Belgium, ZEW Discussion Paper No. 04-55, Mannheim.

Aerts, K. and T. Schmitt (2008), Two for the Price of One? Additionality Effects of R&D Subsidies: A Comparison between Flanders and Germany, Research Policy 37 (5), 806-822.

Aghion, P., N. Bloom, R. Blundell, R. Griffith and P. Howitt (2005), Competition and Innovation: An Inverted-U relationship, The Quarterly Journal of Economics, 701-728.

Aghion, P., P. Howitt and S. Prantl (2011). Patent Protection, Product Market Reforms and Innovative Investments. *mimeo*, Harvard University. http://scholar.harvard.edu/aghion/files/patent_protection_product_market_reforms_and_innovative_investments.pdf

Albert, M.B., Avery, D., Narin, F., and P. McAllister (1991). Direct Validation of Citation Counts as Indicators of Industrially Important Patents. *Research Policy* 20: 251-259.

Almus, M. and D. Czarnitzki (2001), The Effects of Public R&D Subsidies on Firms' Innovation Activities: The Case of Eastern Germany, Journal of Business and Economic Statistics 21(2), 226–236.

Angrist, J.D. (1998), Estimating the Labor Market Impact of Voluntary Military Service Using Social Security Data, Econometrica 66, 249–288.

Arrow, K.J. (1962), Economic Welfare and the Allocation of Resources for Invention, in: R.R. Nelson (ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors, Princeton, N.J., 609–625.

Arvanitis, S., H. Hollenstein and S. Lenz (2002), The Effectiveness of Government Promotion of Advanced Manufacturing Technologies (AMT): An Economic Analysis Based on Swiss Micro Data, Small Business Economics, 19, 321–340.

Berube, C. and P. Mohnen (2009), Are Firms That Received R&D Subsidies More Innovative?, Canadian Journal of Economics 42(1), 206-255.

BMBF (2000), Bundesbericht Forschung 2000*,* Bonn.

Bloom, N. and J. Von Reenen (2002), Patents, Real Options and Firm Performance, The Economic Journals 112, 97-116.

Blundell, R., R. Griffith and J. van Reenen (1995). Dynamic Count Data Models of Technological Innovation. *Economic Journal* 105: 333-345.

BMBF and BMWi (eds.) (2001), Innovationsförderung – Hilfen für Forschung und Entwicklung, Bonn/Berlin.

Branstetter, L. und M. Sakakibara (1998), Japanese Research Consortia: A Microeconometric Analysis of Industrial Policy, Journal of Industrial Economics 46(2), 207–233.

Branstetter, L. und M. Sakakibara (2002), When do Research Consortia Work well and why? Evidence from Japanese Panel Data, American Economic Review 92(1), 143–159.

Busom, I. (2000), An Empirical Evaluation of the Effects of R&D Subsidies, Economics of Innovation and New Technology 9(2), 111–148.

Cerulli, G. (2010), Modelling and Measuring the Effect of Public Subsidies on Business R&D: A Critical Review of the Econometric Literature, Economic Record 86(274), 421-449.

Cerulli, G. and B. Poti (2010), The Differential Impact of Privately and Publicly Funded R&D on R&D Investment and Innovation: The Italian Case, Sapienza – Universita di Roma Doctoral School of Economics Working Paper Nr. 10-2010.

Cincera, M. (1997), Patents, R&D and Technological Spillovers at the Firm Level: Some Evidence from Econometric Count Models for Panel Data, Journal of Applied Econometrics 12, 265–280.

Czarnitzki, D., T. Doherr, A. Fier, G. Licht and C. Rammer (2003). Oeffentliche Foerderung der Forschungs- und Innovationsaktivitaeten von Unternehmen in Deutschland. Studien zum deutschen Innovationssystem.

Czarnitzki, D., B. Ebersberger and A. Fier (2007), The Relationship between R&D Collaboration, Subsidies and R&D Performance: Empirical Evidence from Finland and Germany, Journal of Applied Econometrics 22(7), 1347-1366.

Czarnitzki, D. and A. Fier (2002), Do Innovation Subsidies Crowd out Private Investment? Evidence from the German Service Sector, Konjunkturpolitik - Applied Economics Quarterly 48(1), 1–25.

Czarnitzki, D., A. Fier, O. Heneric, K. Hussinger, G. Licht, E. Müller und W. Sofka (2004), European Competitiveness Report 2004, Competitiveness and Benchmarking, European Commission, Brussels.

Czarnitzki, D. and C. Lopes Bento (2010), Evaluation of Public R&D Policies: A cross country comparison. ZEW discussion paper No. 10-073, Mannheim.

David, P.A. and Hall, B.H. and Toole, A.A. (2000), Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence, Research Policy 29, 497–529.

Dehejia, R.H. and S. Wahba (1999), Causal Effects in Non-experimental Studies: Reevaluating the Evaluation of Training Programs, Journal of the American Statistical Association 94, 1053–1062.

Duguet E. (2004), Are R&D Subsidies a Substitute or a Complement to Privately Funded R&D? Evidence from France using Propensity Score Methods for Non-experimental Data, Revue d'Economie Politique 114(2), 263–292.

European Commission (1996), Community Frame for Public R&D Subsidies, Bruxelles.

European Commission (2003), Investing in Research: An Action Plan for Europe, Commission Staff Working Paper, COM 2003, 226 final, Brussel.

Finger, S.R. (2008), An Empirical Analysis of R&D Competition in the Chemicals Industry'. Available from: http://ssrn.com/abstract=1323919.

Fornahl, D., T Broekel and R. Boschma (2010), What Drives Patent Performance of German Biotech Firms? The Impact of R&D Subsidies, Knowledge Networks and their Location. Papers in Regional Science 90(2), 395-418.

Gelabert, L., A. Fosfuri and J.A. Tribo (2009), Does the Effect of Public Support for R&D Depend on the Degree of Appropriability? Journal of Industrial Economics 57(4), 736-767.

Gonzalez, X., J. Jaumandreu and C. Pazo (2005), Barriers to Innovation and Subsidy Effectiveness, RAND Journal of Economics 36, 930-950.

Gonzalez, X. and C. Pazo (2005), Do Public Subsidies Stimulate Private R&D Spending? Research Policy 37(3), 371-389.

Griliches, Z. (1990), Patent Statistics as Economic Indicators: A Survey, Journal of Economic Literature 28, 1661-1707.

Griliches, Z. and J. Mairesse (1984), Productivity and R&D at the firm level, in: Z. Griliches (ed.), R&D, patents, and productivity, Chicago, 339–374.

Hall, B.H. (1990), The Manufacturing Sector Master File: 1959–1987, NBER Working Paper Series No. 3366, Cambridge, MA.

Hall, B.H., Z. Griliches and J.A. Hausman (1986), Patents and R&D: Is There A Lag?, International Economic Review 27, 1029–1054.

Hall B.H., Jaffe, A. and M. Trajtenberg (2005). Market Value and Patent Citations. RAND Journal of Economics 36, 16-38.

Hall, B.H. and A. Maffiolo (2008). Evaluating the Impact of Technology Development Funds in Emerging Economies: Evidence from Latin America. NBER Working Paper 13835.

Harhoff, D., F. Narin, F.M. Scherer and K. Vopel (1999). Citation Frequency and the Value of Patented Inventions. *The Review of Economics and Statistics* 81(3): 511-515.

Heckman, J.J., H. Ichimura and P. Todd (1997), Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program, Review of Economic Studies 64(4), 605–654.

Heckman, J.J., H. Ichimura and P. Todd (1998a), Matching as an Econometric Evaluation Estimator, Review of Economic Studies 65(2), 261-294.

Heckman, J.J., H. Ichimura, J.A. Smith and P. Todd (1998b), Characterizing Selection Bias Using Experimental Data, Econometrics 66, 1017-1098.

Heckman, J.J., R.J. Lalonde and J.A. Smith (1999), The Economics and Econometrics of Active Labor Market Programs, in: A. Ashenfelter und D. Card (eds.), Handbook of Labor Economics 3, Amsterdam, 1866–2097.

Hussinger, K. (2008), R&D and Subsidies at the Firm Level: An Application of Parametric and Semi-parametric Two-step Selection Models, Journal of Applied Econometrics 23, 729-747.

Jaffe. A.B. (1986), Technological Opportunity and Spillovers of R&D, American Economic Review 76, 984-1001.

Janz, N., G. Ebling, S. Gottschalk und H. Niggemann (2001), “The Mannheim Innovation Panels (MIP and MIP–S) of the Centre for European Economic Research,” Schmollers Jahrbuch – Journal of Applied Social Science Studies 121, 123–129.

Klette, T.J., J. Moen and Z. Griliches (2000), Do Subsidies to Commercial R&D Reduce Market Failures? Microeconometric Evaluation Studies, Research Policy 29, 471–495.

Lach, S. (2002), Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel, Journal of Industrial Economics 50(4), 369–390.

Lach, S. and M. Schankerman (2008). Incentives and Invention in Universities. *RAND Journal of Economics* 39(2): 403-433.

Lechner, M. (1998), Training the East German Labour Force: Microeconometric Evaluations of Continuous Vocational Training after Unification, Heidelberg.

Lechner, M. (1999), Earnings and Employment Effects of Continuous Off-the-job Training in East Germany after Reunification, Journal of Business and Economics Statistics 17, 74–90.

Lechner, M. (2000), An Evaluation of Public Sector Sponsored Continuous Vocational Training in East Germany, Journal of Human Resources 35, 347-375.

Lechner, M. (2001), Identification and Estimation of Causal Effects of Multiple Treatments under the Conditional Independence Assumption, in: M. Lechner and F. Pfeiffer (eds.), Econometric Evaluation of Active Labor Market Policies, Heidelberg, 43–58.

Lerner, J. (1999), The Government as Venture Capitalist: The Long-run Impact of the SBIR program, Journal of Business 72(3), 285–318.

OECD (1993), The Proposed Standard Practice for Surveys of Research and Experimental Development - Frascati Manual, Paris.

OECD (1994), The Measurement of Scientific and Technological Activities - Using Patent Data as Science and Technology Indicators: Patent Manual 1994, Paris.

OECD (2011), OECD Science, Technology and Industry Scoreboard 2011, Paris.

OECD (2012), Main Science and Technology Indicators, Paris.

Pakes A. and Z. Griliches (1984), Estimating Distributed Lags in Short Panels with an Application to the Specification of Depreciation Patterns and Capital Stock Constructs, NBER Working Paper 0933, National Bureau of Economic Research, Cambridge.

Rubin, D. (1974), Estimating Causal Effects of Treatment in Randomized and Non-Randomized Studies, Journal of Educational Psychology 66, 688-701.

Rubin, D. (1977), Assignment to Treatment Group on the Basis of a Covariate, Journal of Educational Statistics 2, 1-26.

Svensson, R. (2013). Publicly-Funded R&D Programs and Survival of Patents. Applied Economics 45, 1343-1358.

Takalo, T., T. Tanayama and O. Toivanen (2008). Evaluating Innovation Policy: A Structural Treatment Effect Model of R&D Subsidies. Bank of Finland Research Discussion Papers 7, Helsinki.

Trajtenberg, M (1990). A Penny for your Quotes: Patent Citations and the Value of Innovations. RAND Journal of Economics 21(1): 172-187.

Wallsten, S.J. (2000), The Effects of Government–Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program, RAND Journal of Economics 31(1), 82–100.

Wooldridge, J.M. (1995), Score Diagnostics for Linear Models Estimated by Two Stage Least Squares. In Advances in Econometrics and Quantitative Economics: Essays in Honor of Professor C. R. Rao, ed. G. S. Maddala, P. C. B. Phillips, and T. N. Srinivasan, 66–87. Oxford: Blackwell.

Zuniga-Vicente, J.A., C. Alonso-Borrego, F.J. Forcadell and J.I. Galan (2014). Assessing the Effect of Public Subsidies on Firm R&D Investment: A Survey*,* Journal of Economic Surveys, 36-67.

Appendix

This section presents IV regressions to show that our findings are robust if selection on unobservables into account when the treatment effect of the treated is estimated. The results also show robustness if the amount of funding is taken into account rather than a subsidy dummy. We estimate 2SLS for *RD* and *NETRD*. In the first specification, we use a dummy for the receipt of public subsidies. In the second specification, we take the subsidy amount into account. The subsidy dummy/amount are treated as endogenous. As instruments we use the number of subsidized projects and the average amount per subsidized project per firm in the past three years. The subsidies received in the past should impact the current receipt of subsidies since firms that received subsidies already know the application procedure so that they are more likely to apply again. Furthermore, if they completed subsidized projects successfully in the past they should be more likely to receive funding again. Past subsidies should not impact recent R&D investments since the subsidies are only apply for the specific funded project. In order to receive money from the funding agency the firm has to hand in a receipt to proof the purpose of the investment. Hence, there should be no impact on current R&D spending. The instruments are also valid and relevant from a statistical point of view as the tests presented at the bottom of Table 6 show.

Taking selection on unobservables into account comes at the cost of imposing a functional form assumption for the R&D investment equation. Table 6 shows the estimated coefficients for the variables in the R&D investment equations.

Table 6 about there

The estimated effects are in line with our expectations. Technology-intense firms, as captured by their patent stock invest more in R&D. There is a U-shaped effect of firm size, indicating the presence of small technology-intense firms and large firms with many innovation projects in our sample. There is some evidence for firms located in East Germany to spend less on R&D. There is a negative effect of firm age. Firms belonging to a firm group spend less on R&D. A positive impact appears for the firms' export intensity. Firms competing international have stronger incentives to innovate due to fiercer competition. Industry and time dummies are jointly significant as LR-tests at the bottom of Table 6 show.

The dummy for the receipt of subsidies and the subsidy amount are significantly positive. Results from a Wooldridge score test (Wooldridge, 1995) show that they are endogenous in all specifications. Staiger and Stock (1997) emphasize that endogeneity tests can be misleading in case of weak instruments. In case of weak instruments the correlation between the instrument and the endogeneous variable can be artificially high due to the presence of other control variables. Staiger and Stock (1997) suggest evaluating the partial correlation of the instruments and the endogenous variable. As a rule of thumb, they state that the partial F-statistic should exceed the value of 10 to ensure that the instruments are not weak. Table 6 shows that the partial F-statistics for the instruments in all specifications exceed 10 indicating that the instruments have significant additional explanatory power for firms' R&D intensity. Hence, we conclude that our instruments are not weak.

Table 6 further presents overidentification tests based on the score test by (Wooldridge, 1995). The fact that the number of instruments exceeds the number of endogenous regressors, i.e. the model is overidentified, requires testing whether the instruments are uncorrelated with the error term. Overidentification tests deal with two hypotheses at the same time: first, they test whether the instruments are uncorrelated with the error term and, second, whether the model is incorrectly specified. Table 6 shows that the test statistics are not significant for all specifications, indicating that we cannot reject invalidity of our instruments at any convenient level of statistical significance. This result also makes us confident about our model choice.

Under the assumption that the stochastic parts of the R&D investment of funded and non-funded firms are the same we can interpret the coefficient of the subsidy dummy as the treatment effect on the treated (Wooldridge, 2000). We employ this assumption to take the IV regression results as an input for the patent outcome equation. Table 7 shows the results. We again find that publicly sponsored R&D is as productive as private R&D.

Table 7 about there

Tables & Figures

Figure 1: R&D Subsidies

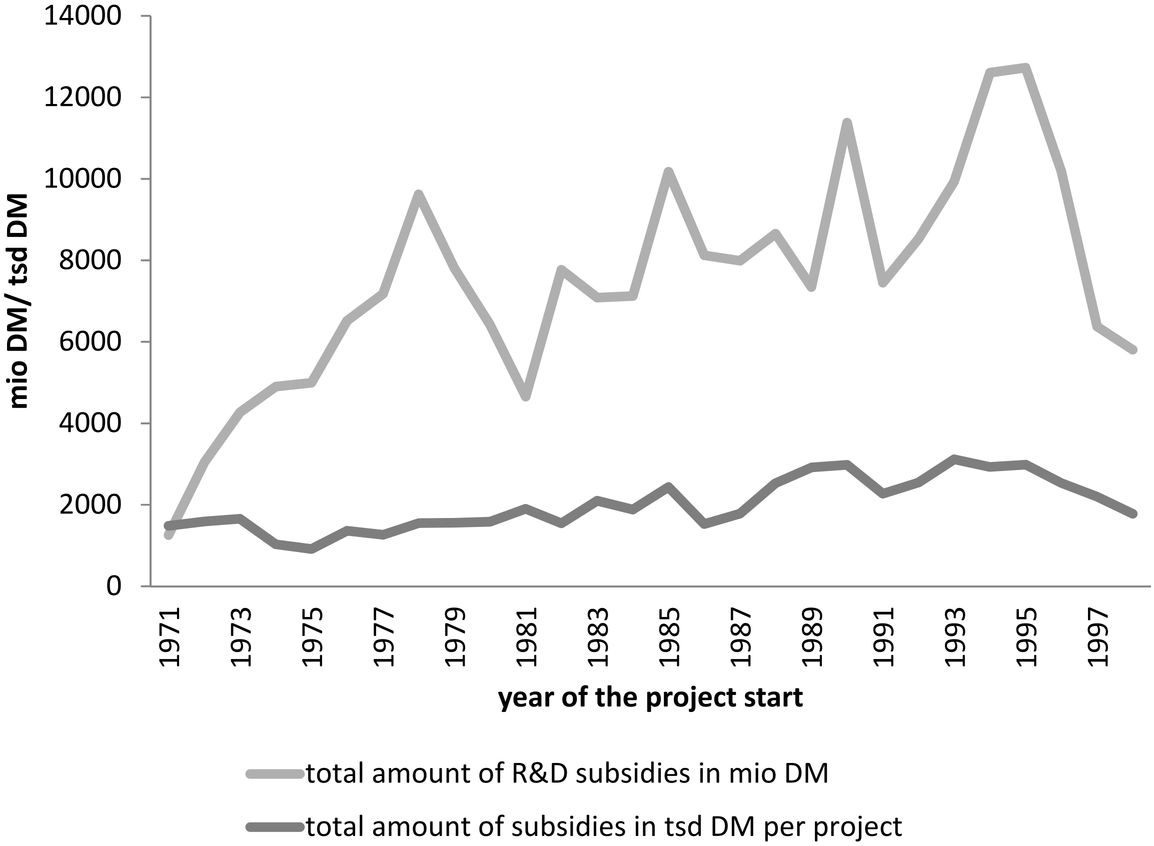

Table 1: The Matching Protocol

Step 1	Specify and estimate a probit model to obtain propensity scores *P(X'β)*.
Step 2	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.
Step 3	Choose one observation *i* from the subsample of treated firms and delete it from that pool.
Step 4	Take the estimated propensity score *P(X'β)*. 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 *v* (where *v* is a subset of *X*) that contains important matching variables. The variant is called hybrid matching (Lechner, 1988).
Step 5	Calculate the Mahalanobis distance between treated firm *i* and all nontreated firms *j* in order to find the most similar control observation. Let: $d_{ij} = \left(P\left(x_i'\hat{\beta}\right), v_i\right) - \left(P\left(x_j'\hat{\beta}\right), v_j\right) \forall\, j = 1, \dots, N^C$ The Mahalanobis distance equals: $MD_{ij} = {d_{ij}}'\,\Omega\, d_{ij} \quad \forall\, j = 1, \dots, N^C$ To find the nearest neighbor. *Ω* represents the covariance matrix based on the controls, i.e. firms that did not receive public subsidies.
Step 6	After calculating the distance, one can impose additional restrictions on the neighborhood. For instance, we require that for being a neighbor of participant *i*, a potential control firm has to e recorded in the same industry sector. Firms in other industries are deleted from the potential control group.
Step 7	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.
Step 8	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 potential control firms. With a larger pool of potential control observations one could also draw without replacement.
Step 9	Repeat steps 3 to 7 to find matched pairs for all recipients of R&D subsidies.
Step 10	Using the matched comparison group, the average treatment effect on the treated is calculated as the mean difference of the matched samples: $\hat{\alpha}^{TT} = \frac{1}{N^T}\left(\sum_{i=1}^{N^T} R\&D_i^T - \sum_{i=1}^{N^T} \widehat{R\&D}_i^C\right).$ As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t-statistic on mean differences 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.

Table 2: Descriptive Statistics

	Funded firms $N^T = 586$		Non-funded firms $N^C = 3,188$			
	mean	s.d.	mean	s.d.	mean difference	
PATENT	1.53	2.82	0.64	1.82	0.88	***
CITPAT	2.84	7.62	1.15	5.43	1.69	***
RD	4.08	5.67	1.77	3.69	2.31	***
NETRD	3.84	5.59	1.77	3.69	2.07	***
RD/SALES	6.23	7.59	3.14	4.86	3.09	***
NETRD/SALES	5.31	6.36	3.14	4.86	2.17	***
PS/EMP (lagged)	0.03	0.06	0.02	0.04	0.01	***
ln(EMP)	5.67	1.23	5.02	1.34	0.65	***
EAST	0.36	0.48	0.16	0.36	0.21	***
ln(AGE)	2.85	1.32	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	0.17	0.94	0.23	0.03	***
EXPORT	0.32	0.25	0.25	0.23	0.07	***
IMPORT	0.31	0.22	0.28	0.22	0.03	***
HHI	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).

Table 3: Probit Estimation for the Receipt of Public R&D Subsidies (# obs. 3,774)

	coef.		s.e.	marg. eff.[a]		s.e.
PS/EMP (lagged)	3.85	***	0.58	0.69	***	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	-0.18		0.18	-0.03		0.03
CAPCOM	0.02		0.15	0.00		0.03
EXPORT	0.24	*	0.13	0.04	*	0.02
IMPORT	0.18		0.32	0.03		0.06
HHI	-0.29		0.44	-0.05		0.08
constant	-4.32	***	0.30			
LR-tests for joint significance:						
Industry dummies			$X^2(12) = 148.07$***			
Time dummies			$X^2(6) = 47.13$***			
Log Likelihood			-1,295.88			
McFadden R^2			0.20			

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

[a] Marginal effects are calculated at the sample means.

Table 4: Results for the NN-matching

	Funded firms $N^T = 571$	Non-funded firms $N^C = 571$			
	mean	mean	mean diff.		s.e.
PS/EMP (lagged)	0.03	0.02	0.01		0.00
ln(EMP)	5.68	5.67	0.01		0.09
EAST	0.35	0.35	-0.00		0.04
ln(AGE)	2.86	2.88	-0.02		0.10
GROUP	0.32	0.32	-0.00		0.03
FOREIGN	0.04	0.03	-0.01		0.01
CAPCOM	0.97	0.97	0.00		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	0.32	0.32	0.00		0.01
RD	4.07	2.97	1.10	***	0.38
RD/SALES*100	6.26	4.38	1.88	***	0.52
ln(RD)	0.53	0.02	0.51	***	0.12
NETRD	3.84	2.97	0.87	**	0.37
NETRD/SALES*100	5.34	4.38	0.96	**	0.49
ln(NETRD)	0.31	0.02	0.29	***	0.12

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

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 firms. The samples are also balanced with respect to time (6 time dummies not presented).

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

Table 5: Estimation of the Patent and Citation Equation

Dep var:	PAT	PAT	CIT	CIT
	poisson	poisson	poisson	poisson
	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
$\widehat{RD}^{C}$	0.09***	0.08***	0.11***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
TT	0.09***	0.06***	0.11***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
EAST	-0.88***	-0.65***	-1.00***	-0.78***
	(0.13)	(0.14)	(0.20)	(0.18)
Pre-sample mean		0.15***		0.07***
		(0.05)		(0.02)
Constant	-2.08***	-2.31***	-1.77	-2.05*
	(0.32)	(0.35)	(1.58)	(1.12)
LR tests on joint significance				
industry dummies	600.41***	446.28***	1,512.04***	1,286.80***
time dummies	30.71***	51.01***	116.88***	230.14***
X^2-test: $\widehat{R}^{C}$= TT	0.03	13.88***	1.25	34.06***
# obs.	3,759	3,759	3,759	3,759
Log Likelihood	-4,960.02	-4,345.05	-9,995.26	-8,676.82
X^2	509.42	1,048.22	508.84	1,093.15

***,**,* indicate a significance level of 1%, 5%, 10%.
Standard errors are bootstrapped. 200 replications are used.

Table 6: IV Regressions for the Average Treatment Effect on the Treated

Dependent variable	RD	RD	NETRD	NETRD
	coeff.	coeff.	coeff.	coeff.
	(s.e.)	(s.e.)	(s.e.)	(s.e.)
FUNDED	2.75***		2.06***	
	(0.72)		(0.69)	
AMOUNT FUNDING		4.03***		3.03**
		(1.49)		(1.49)
PS/ EMP	6.25***	7.01***	6.45***	7.01***
	(1.46)	(1.36)	(1.43)	(1.36)
ln(EMP)	-3.99***	-3.89***	-3.97***	-3.89***
	(0.34)	(0.34)	(0.34)	(0.34)
$\ln(EMP)^2$	0.54***	0.54***	0.54***	0.54***
	(0.04)	(0.04)	(0.04)	(0.04)
EAST	-0.64***	-0.24	-0.54**	-0.24
	(0.23)	(0.19)	(0.22)	(0.19)
ln(AGE)	-0.30***	-0.26***	-0.29***	-0.26***
	(0.07)	(0.07)	(0.07)	(0.07)
GROUP	-0.46**	-0.27*	-0.41**	-0.27*
	(0.19)	(0.17)	(0.18)	(0.17)
FOREIGN	-0.17	-0.18	-0.17	-0.18
	(0.35)	(0.31)	(0.34)	(0.31)
CAPCOM	-0.17	-0.18	-0.17	-0.18
	(0.26)	(0.27)	(0.26)	(0.27)
EXPORT	0.93***	1.03***	0.96***	1.03***
	(0.27)	(0.26)	(0.26)	(0.26)
IMPORT	-0.38	-0.36	-0.37	-0.36
	(0.55)	(0.54)	(0.54)	(0.54)
HHI	2.34**	2.49**	2.37**	2.49**
	(1.03)	(1.05)	(1.03)	(1.05)
Constant	6.77***	6.17***	6.62***	6.17***
	(0.74)	(0.72)	(0.74)	(0.72)
LR-tests for joint significance:				
Industry dummies	120.27***	195.29***	136.57***	195.29***
Time dummies	25.25***	20.81***	24.05***	20.81***
F-test for relevance of the instruments:	26.23***	26.23***	13.06***	13.06***
Wooldridge score test for overidentification:	0.40	0.11	0.33	0.11
Wooldridge score test for endogeneity:	8.23***	4.12**	5.70**	4.13**
# obs.	3774.00	3774.00	3774.00	3774.00
R^2	0.37	0.39	0.38	0.38

***,**,* indicate a significance level of 1%, 5%, 10%.
Standard errors are robust.

Table 7: Estimation of the Patent and Citation Equation: $\widehat{R}^{C}$ and *TT* Determined by IV Regressions

Dep var:	PAT	PAT	CIT	CIT
	poisson	poisson	poisson	poisson
	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)	coeff. (s.e.)
$\widehat{RD}^{C}$	0.09*** (0.01)	0.08*** (0.01)	0.11*** (0.01)	0.10*** (0.01)
TT	0.09*** (0.01)	0.07*** (0.01)	0.10*** (0.01)	0.09*** (0.01)
EAST	-0.79*** (0.12)	-0.57*** (0.12)	-0.93*** (0.17)	-0.73*** (0.16)
Pre-sample mean		0.15*** (0.04)		0.06*** (0.02)
Constant	-2.11*** (0.31)	-2.32*** (0.32)	-1.80** (0.94)	-2.05* (0.93)
LR tests on joint significance				
industry dummies	609.25***	436.24***	1,519.92***	1,258.29***
time dummies	30.65***	49.12***	116.78***	214.39***
X^2-test: $\widehat{R}^{C}$= TT	0.10	0.77	0.73	1.44
# obs.	3,774	3,774	3,774	3,774
Log Likelihood	-5,024.12	-4,398.29	-10,048.57	-8,743.55
X^2	515.53	1,134.42	525.08	1,039.58

***,**,* indicate a significance level of 1%, 5%, 10%.
Standard errors are bootstrapped. 200 replications are used.
The estimated TT is based on the first specification in Table 7.