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The Effects of Public R&D Subsidies on Firms' Innovation Activities: The Case of Eastern Germany

Matthias Almus and Dirk Czarnitzki

ZEW

Zentrum für Europäische
Wirtschaftsforschung GmbH

Centre for European
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Matthias Almus and Dirk Czarnitzki

Centre for European Economic Research (ZEW), Mannheim

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Abstract

This study analyzes the effects of public R&D policy schemes on the innovation activities of firms located in Eastern Germany. The main question in this context is whether public funds stimulate R&D activities or simply crowd out privately financed R&D. Empirically, we investigate the average causal effects of all public R&D schemes in Eastern Germany using a non–parametric matching approach. Compared to the case where no public financial means are provided, it turns out that firms increase their innovation activities by about four percentage points.

Keywords: Public Innovation Subsidies, Non–parametric Matching.

JEL Classification: C41, O31, O38.

address: Centre for European Economic Research (ZEW)
Department of Industrial Economics and International Management
P.O.Box 10 34 43, D–68034 Mannheim
phone: +49/621–1235–185, –158
fax: +49/621–1235–170
e–mail: almus@zew.de, czarnitzki@zew.de

1 INTRODUCTION

In 1998, the German federal government spent about 2.2 billion Euro on promoting R&D activities in the business sector. Given this large amount of public R&D subsidies for innovation projects the question arises of whether policy schemes stimulate private activities that produce positive externalities, i.e. benefits to society.

The economic literature concerning external effects indicates that innovation projects lead to market failures. Innovations are assumed to have positive external effects, but firms only launch privately profitable innovation projects. Thus, there may be projects that would have positive benefits to society, but do not cover the private cost. Therefore, these projects are not carried out and the quantity of innovations is below the socially desirable level. This circumstance 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 always has an incentive to apply for public R&D support, even if 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.

This study investigates the effects of R&D subsidies in Eastern Germany which is more than a decade after the break down of the Berlin Wall still a transition economy. Public authorities have been trying to accelerate the transition process from a planned economy to a market economy since the German reunification in 1990. The efforts undertaken were and still are enormous but many industrial firms are still struggling to survive. In most regions of Eastern Germany, the number of producing firms per inhabitant is far below the average of West Germany. Moreover, firms are mostly too small, i.e. they have not reached the minimum efficient size of production (MES). Furthermore, firms suffer from the collapse of "eastern markets" which still induces severe sales difficulties. To overcome these difficulties various programs and schemes have been set up.

For example, Ragnitz (2000) compares all subsidies granted in Eastern and Western Germany. In relation to the labor force, the amount is twice as high in Eastern Germany. Instead of the labor force, one can also consider subsidies in relation to the gross domestic product. In this case, subsidies are more than three times higher in Eastern Germany than in Western Germany. According to calculations of Ebling et al. (1999), about 60% of innovating firms in Eastern Germany received public R&D funding in 1996. This quote is six times higher than in the western part of Germany. Moreover, there are considerably more means spent on new firms to establish a certain amount of small and medium sized firms (SME) that are important for a powerful market economy (Almus 2001). These figures make an examination of public R&D schemes in Eastern Germany an interesting and necessary task. Therefore, in this paper we analyze whether a crowding–out effect among public R&D funds and privately financed R&D activities occurs in the Eastern German economy.

2 THIS STUDY IN CONTEXT OF EXISTING LITERATURE

Several empirical studies already exist on the effects of public R&D subsidies. David et al. (2000) review the literature on the relation between R&D subsidies and R&D expenditure on different levels of aggregation. All studies reviewed aim to explore the sign and the magnitude of the "net" effect of public policies. On industry or country level only 2 out of 14 empirical studies report that public R&D funding crowds out private R&D investment. The evidence is less clear at the firm level: 9 out of 19 studies indicate substitutional effects, i.e. public funds crowd–out private investment either partially or even completely.

The difficulty of this kind of analysis are potential selection biases coming from the public institutions that — depending on the applying firm and the relevant R&D project — decide the recipients of the public funding solely: "This makes public funding an endogenous variable, and its inclusion in a linear regression will cause inconsistent estimates if it happens to be correlated with the error term" (Busom, 2000: 114). Furthermore, public institutions might support only those firms and R&D projects that are expected to generate extensive economic spillover effects. To estimate the "real" effects of public subsidies it is therefore necessary to address the core evaluation question: How much would the subsidy receiving firms have invested, if they had not participated in a public policy scheme? In fact, only a few studies on the impact of R&D subsidies attempt to model this counterfactual situation. Most of the studies surveyed in David et al. (2000) do not pay attention to this kind of selection bias.

Recently, Wallsten (2000) considers a simultaneous equation model to pay attention to the possible interdependence between public R&D funding and R&D expenditure of firms. He investigates the Small Business Innovation Research (SBIR) program and concludes that it is necessary to account for possible endogeneity of federal R&D grants. According to the results of the study SBIR awards crowd out firm–financed R&D spending dollar for dollar (full crowding–out). The subsidies do neither have an effect on R&D activities nor on employment. However, he mentions another possible and important impact of public funding: "[...] while the grants did not allow firms to increase R&D activity, they instead allowed firms to continue their R&D at a constant level rather than cutting back." (Wallsten, 2000, p. 98).

Busom (2000) explores the problem of selection bias by applying a two stage econometric treatment model where the first stage consists of estimating a probit model on the participation probability in public funding programs. In the second stage, the R&D activity is regressed on several covariates including a selection term which accounts for the different propensities of firms to be publicly funded. This second equation is estimated separately for participants and non–participants. The difference in expected R&D expenditure of both groups is according to this approach the result of public funding. Busom concludes that for the majority of firms in her sample public funding induced more R&D activities, but for 30% of participants complete crowding–out effects cannot be ruled out.

Lach (2000) investigates the effects of R&D subsidies granted by the Israeli Ministry of Industry and Trade on local manufacturing firms. He applies different estimators, such as the before–after–estimator, the difference–in–

difference estimator and different dynamic panel data models. Although Lach finds heterogenous results from different models applied, he finally concludes that subsidies do not crowd out company financed R&D expenditure completely. Their long–run elasticity with respect to R&D subsidies is 0.22.

Other microeconomic approaches do not focus on crowding–out effects but take different output measures into consideration: for example, the effects of subsidies on patent applications, productivity, fixed asset investments, returns on capital, returns on sales and growth of sales or employment (see Klette 2000 for a comprehensive survey).

This study focuses on the crowding–out issue and introduces another empirical tool to the literature on examining the effects of public R&D funding. We apply a non–parametric matching approach that goes back to the model of potential outcomes developed by Roy (1951) and Rubin (1974). These matching approaches were extensively applied in the literature on the evaluation of labor market policies, e.g. the evaluation of active labor market programs (ALMP) or qualification measures (LaLonde 1986, Dehejia and Wahba 1999, Lechner 1999, Heckman et al. 1999). In these cases, people are the subject of the examination and research questions include whether wages, salaries or the probability of being hired or re–employed increase if people take part in a specific measure or program. The non–parametric matching approach applied here can clearly identify the effect that goes back to the receipt of public R&D funding, since we are able to approximate a situation where no differences exist between subsidized and non–subsidized firms with respect to characteristics that influence the probability to receive public support and to carry out private R&D. According to Hausman (2001) the matching methodology leads to more robust estimates of the treatment or causal effect compared to alternative approaches.

A major advantage of this study is the ability to identify exactly whether a firm received any subsidies for innovative projects. All programs launched by public authorities are incorporated and so the approach applied can reflect the effects of public R&D policy schemes collectively and is not restricted to a particular measure. Many other studies only deal with one specific public

R&D program and cannot control for possible effects of other publicly funded research. In contrast, we can distinguish recipients and non–supported firms in the sample exactly. Our control group contains only firms which did not receive any public R&D grants. This is not the case for several other studies that analyze one specific R&D program but are not able to control for other sources of public funding. However, this advantage has its price: We are not able to track in which particular program a firm participated. We only observe whether a firm participated in any public R&D scheme under consideration. Therefore, we do not describe the R&D programs in more detail. Of course, the treatments were targeting different types of firms or aims and thus heterogeneous treatments exist. Hence, our study can only be seen as broad evidence on the overall R&D policy in Eastern Germany and is only able to discover average effects over different schemes.

3 DATA

The data used is taken from the Mannheim Innovation Panel (MIP) conducted by the Centre of European Economic Research (ZEW) on behalf of the German Federal Ministry for Education and Research (cf. Janz et al. 2001 for a more detailed description of the MIP database). The MIP is a German survey on innovation activities in the business sector. It formed the German part of the Community Innovation Survey (CIS) of the European Commission in 1993, 1997 and 2001. Since 1993 information from about 2,500 German manufacturing firms has been collected in the MIP annually. We use data from the surveys in 1995, 1997 and 1999, i.e. the information collected corresponds to the firms' activities in 1994, 1996 and 1998. Firms in the survey are from almost the whole business sector and can be classified according to the European standard classification NACE. We use the manufacturing sector and, thus, firms in the sample belong to twelve industries that are characterized by dummies in the empirical analysis (see Table 5 in the appendix). Note that only firms with at least five employees are sampled in the MIP. In critique of former studies, Lichtenberg (1984) argues that the results of evaluations are often biased because the data used is mainly comprised of observations on large firms. The MIP data overcome this problem as there are many observations on small and medium sized firms (see descriptive statistics). The sample contains 925 observations on innovating firms located in Eastern Germany from which 622 participated in public R&D schemes. Note that we use our database not as panel data but as three cross–sections. Most firms, i.e. more than 70%, are only observed once in the sample. Only about 8% are included in every of the three cross–sections. Table 1 contains descriptive information on participating firms and the potential control group of non–participants. According to the Oslo–Manual guidelines (Eurostat and OECD 1997) innovators are defined as firms which have introduced at least one product or process innovation in recent three years. A product or process innovation is defined as follows:

> "Technological product and process (TPP) innovations comprise implemented technologically new products and processes and significant technological improvements in products and processes. A TPP innovation has been implemented if it has been introduced on the market (product innovation) or used within a production process (process innovation). TPP innovations involve a series of scientific, technological, organizational, financial and commercial activities. The TPP innovating firm is one that has implemented technologically improved products or processes during the period under review." (Eurostat and OECD 1997, p. 47)

As potential outcome variable in the empirical analysis, the R&D intensity is considered, i.e. the ratio of R&D expenditures to sales (multiplied by 100). We separate our sample with respect to the participation in public R&D schemes into the treatment group, i.e. subsidized firms, and potential control group. The empirical analysis then tries to assess whether firms that received public R&D funds in 1994, 1996 or 1998 have on average a higher R&D intensity compared to firms that did not receive public means in the period under consideration. There are three time periods under evaluation and a firm may belong to the group of subsidized firms (treatment group) in one, two or all three periods. However, we only allow firms to enter the potential control group if they have previously not participated in any of the R&D support programs. Hence, all firms that received public R&D funds in 1994 but not in subsequent years under examination or in 1996 but not in 1998 are excluded from the potential control group to avoid biased results. An important part of the empirical analysis is to estimate the probability of a firm to receive public funds given a number of observable characteristics which also have an influence on the success variable, i.e. the R&D intensity. Therefore, several control variables that are used in the empirical analysis are presented briefly in the following paragraphs.

The log of the number of employees and its square take account of possible size effects. A potential concern of using the number of employees is the fact that firms which receive subsidies may hire R&D staff and thus their employment increases. This would cause some endogeneity among the receipt of public funding and firm size. Therefore, it would be preferable to use the lagged number of employees of the year prior to participation in public policy schemes but we do not have the required information in our database. However, we think that the possible endogeneity problem is not severe in our study for two reasons: First, there are only a few programs elaborated towards increasing the R&D staff directly. Second, R&D staff as a proportion of all employees of the firm amounts to less 5% on average for the firms in the database, where this figure is quite stable over time. Hence, R&D subsidies may influence the number of R&D staff in some cases but this change is small compared to the number of all employees. These two arguments weaken the concern of a potential endogeneity between the receipt of R&D subsidies and the number of employees.

Eleven industry dummies control for cross–sectional differences, e.g. different technological potential in various industries. Two cohort dummies shift inter–temporal effects. Another important factor that might have an influence on the probability of funding as well as on the success measure is market competition. Thus, several variables control for competitive impacts: the market share variable measures the firms' sales in relation to the industries' sales measured on the NACE three digit level. The import ratio measured on the two digit sectoral level captures the competitive pressure of foreign firms on the market. Moreover, we consider the firms' export related sales divided by total sales to measure foreign competition. The sellers concentration on the domestic market is also taken into account. This is measured as the concentration ratio CR6, i.e. the sum of market shares of the industries' six largest firms. Capital intensity, i.e. the ratio of tangible assets per employee, is included in the analysis to control for different technologies used in the production process. Moreover, we incorporate the firms' age. It is often claimed that older firms are more reluctant to pursue innovation and, thus, one may argue they are less likely to apply for public research programs. The foundation of a firm usually induces innovation activities and, hence, young firms are expected to be more lively regarding R&D.

The legal form indicates the attitude of the firm (owner) towards risk and also the chance to enter public R&D programs. Hence, the dummy variable 'legal form' separates the sample in firms with liability limiting legal forms (joint stock company [AG], non–public limited liability firm [GmbH] or commercial partnership with a non–public limited liability firm [GmbH & Co.KG]). For these firms the legal form dummy is zero. Using these legal forms owners can minimize their risk up to a certain amount and thus have higher incentives to pursue more risky projects (Stiglitz and Weiss 1981). The dummy is one for firms with remaining legal forms (joint partnerships etc). Companies with limited liability have much better options to receive public subsidies because if firms apply for public grants, they have to prove that they maintain an operating industrial plant. Firms with a liability limiting legal form have to be recorded in the trade register in Germany which means a publicly available information exists that this firm is already doing its business. Companies with other legal forms have to prove this within their application for public grants and the ministry official has to inspect this on her or his own. Due to the fact, that ministy officials may behave risk averse, companies with limited liability are possibly favored because they have already proved their credibility.

To control for technological prowess or previous R&D experience a dummy variable, indicating if firms have R&D departments, enters the analysis. The inclusion of this dummy holds the potential of creating an endogeneity problem. However, this would only be the case if firms in the sample were establishing new R&D departments as a result of the receipt of public subsidies. As there are no public R&D schemes in Germany which explicitly support the founding of whole R&D departments, the endogeneity problem is unlikely to occur. However, the R&D department dummy reflects the absorptive capacity and R&D experience of firms. The use of other variables is not possible with our data: Unfortunately, using the (share of) R&D

personnel would cause endogeneity problems because there are some policy schemes which promote hiring R&D staff. Other indicators of absorptive capacity like lagged values of R&D expenditure are not available.

Finally, we incorporate dummy variables that indicate if the observed firm is a subsidiary of a foreign or West German firm. This is done for two reasons: There are many policy schemes especially for small and medium sized firms (SME). However, if a firm is an SME but also belongs to a group with a large parent company, this firm would not be accepted to participate in policy schemes designed for SME. Moreover, many schemes are exclusively for Eastern German firms, but if the parent company is a western one, the subsidiaries are not allowed to enter in programs for Eastern German firms. Hence, the dummy variables 'Western German parent company' and 'foreign parent company' should capture these effects.

4 IDENTIFICATION AND MATCHING

4.1 Causal Effects and Potential Results

The situation to be examined is typical for an evaluation. All firms in the database can be separated with respect to the receipt of public R&D subsidies. This leads to a non–experimental setting since the receipt of subsidies is not random. There are several differences between the groups of firms with and without R&D subsidies as the upcoming empirical analysis will reveal. The receipt of public R&D subsidies finally leads to a potential outcome Y^1 for the firms that received subsidies and Y^0 for the non–recipients. The approach that is used to measure the difference between groups, i.e. the causal effect, goes back to the model of potential outcomes by Roy (1951) and Rubin (1974). Rubin defined the term causal effect as: "[...] the difference between the likely outcome of a person's participation in the measure and the likely outcome of a person's non participation." The participation of firm i in any R&D scheme is denoted with $S_i = 1$ and $S_i = 0$ otherwise. The evaluation aims to calculate the causal effect of public R&D schemes in the subsidised firms' view, i.e. the study concentrates on the causal effect θ^1 that results from receiving R&D subsidies:

$$\theta^1 := E[Y^1 - Y^0|S = 1] = E[Y^1|S = 1] - E[Y^0|S = 1] \tag{1}$$

where $E[\bullet]$ in equation (1) represents the expectation operator. The causal effect then indicates whether public R&D support has a positive impact on the private R&D intensity. However, the outcome $E[Y^0|S = 1]$ is by definition not observable, since non–subsidised firms cannot be observed in the case of R&D subsidy receipt. The first outcome $E[Y^1|S = 1]$ can be estimated unbiased as the mean value of the outcome variable representing firms that received subsidies. To identify $E[Y^0|S = 1]$ we have to incorporate further assumptions.

4.2 Identification

$E[Y^0|S = 1]$ cannot simply be calculated as arithmetic mean of the non–recipients since:

$$E[Y^0|S = 1] \neq E[Y^0|S = 0] \quad . \tag{2}$$

This condition would only be valid in the case of an experiment where participants and non–participants are randomly assigned to the measure. The descriptive analysis, however, shows that subsidized and non–subsidized firms in our sample differ in various important characteristics. Due to selection processes on the part of the authorities that decide how to distribute the funds among applicants, the group of firms that received assistance is a special and selective one. Moreover, firms have different information and different access to information regarding possibilities of application for public funds. This may be a further source of potential selection.

Rubin (1977) introduces the conditional independence assumption (CIA) to solve the problem arising in equation (2). This condition means that participation (receipt of subsidies) and potential outcome (R&D intensity) are independent for individuals with the same set of exogenous characteristics $(X = x_i)$:

$$(Y^0, Y^1) \perp S|X = x \qquad (CIA) \quad . \tag{3}$$

The condition helps to overcome the problem that $E[Y^0|S = 1]$ is unobservable. If CIA is valid, $E[Y^0|S = 0, X = x_i]$ can be used as a measure of potential outcome for the R&D recipients (Lechner 1998). CIA, however, is only plausible if all variables that influence the outcome Y^0 or Y^1 and the participation status S are known and available in the data set. While it is not possible to test the validity of CIA formally (see Almus et al. 1999), the MIP contains a rich set of information that we believe makes the CIA a reasonable approximation. If CIA is correct the equation:

$$E[Y^0|S = 1, X = x] = E[Y^0|S = 0, X = x] \tag{4}$$

holds, which means that the outcome of non–participants can be used to calculate the average outcome for the participants in an unbiased way provided that there are no systematic differences between firms with and without public R&D subsidies. Then, the causal effect of public subsidization in equation (1) changes to:

$$\theta^1 := E[Y^1|S = 1, X = x] - E[Y^0|S = 0, X = x] \tag{5}$$

which can be estimated unbiased using the means of both groups (Lechner 1998). The next step requires a search for pairs of non–subsidized and subsidized firms that do not differ in characteristics contained in the vector X. Here, the study deviates from other examinations. Normally, there are more firms or individuals in the potential control group compared to the group of treated individuals or firms. Our database, however, has about twice as many firms that received public R&D subsidies than non–recipients due to the special situation in Eastern Germany after reunification. Then, the matching approach assigns to every subsidized firm a similar non–subsidized counterpart. Using this approach we do not waste information of subsidized firms. However, a non–subsidized firm may be matched to more than one recipient of R&D subsidies.

4.3 Non–parametric Matching

Rosenbaum and Rubin (1983) point to the fact that a large number of exogenous characteristics is required to ensure the validity of the CIA. The vector x_i containing the exogenous variables of firm i therefore has a high dimension. This impedes the estimation of the causal effect, since it is almost impossible to find subsidized and non–subsidized firms that have exactly the same values in the exogenous variables if there are many to consider. Fortunately, the vector of exogenous variables x_i can be condensed into a single scalar measure to solve this problem, the so called propensity score. This measure represents the probability that a given firm i has received public R&D subsidies at all given a set x_i of individual characteristics $Pr(S_i = 1|X = x_i)$. Rosenbaum and Rubin (1983) show that if the CIA is fulfilled, it is sufficient to condition on the propensity score to ensure statistical independence between potential outcome and receipt of R&D subsidies. There are several forms of conditioning that can be summarized under the term balancing scores (Rosenbaum and Rubin 1983, Lechner 1998). Balancing scores cover a wide range of measures starting from the most complex $X = x_i$ to the propensity score $Pr(S_i = 1|X = x_i)$ as most simple form. This analysis uses the unbounded propensity score $x_i'\hat{\beta}$ as single matching criterion.

Beside the independence between potential outcome (firm specific R&D intensity) and participation status (receipt of public R&D funds) the identification of the causal effect depends on a further condition. Individual causal effects may not be influenced by the participation status of other firms, i.e. the absence of indirect effects (SUTVA [stable unit treatment value assumption] condition) (Angrist et al. 1996). SUTVA constitutes a potential caveat of the analysis but since all R&D programs in Eastern Germany are considered these possible indirect effects should not cause biased results: The firms compete for the means on many sub–markets (various schemes). Regarding a possible demand shift for R&D inputs and thus a change in factor prices, we do not believe that public policy schemes have a remarkable effect. In our opinion, the market for R&D inputs can be seen as a national market rather than several regional ones. Admittedly, a proportion of 60% of innovating firms was subsidized in Eastern Germany but when looking at whole Germany this proportion is rather small, because less than 14% of German innovators are located in Eastern Germany. In Western Germany only about 15% of innovating firms receive any public funding. Thus, the majority of German innovators in the manufacturing sector does not participate in public R&D schemes. Moreover, the amount of subsidies for the recipients is low compared to their private investments. For example, in 1999, firms spent on R&D activities about DM 60 billion in Germany, while the public R&D subsidies of the federal government amounted to about DM 2 billion for civilian R&D (BMBF 2000). Unfortunately, there are no figures available for Eastern Germany only. However, as the share of subsidies is only about

3%, it seems to be unlikely that public R&D schemes have a significant influence on prices for R&D inputs. Hence, the SUTVA is assumed to be fulfilled.

Other approaches that can be used to estimate the causal effect in non–experimental settings exist. The most often applied are (for a comprehensive overview cf. Heckman et al. 1999):

- The "difference–in–differences" method (Ashenfelter 1978, Ashenfelter und Card 1985) became popular with the availability of panel data. Here, potential selection biases stemming from observable time invariant variables vanish in the linear model if differences are calculated over time (Fitzenberger und Prey 1998).
- Complete econometric selection models simultaneously estimate participation and success of the program or measure. These models depend on restrictive assumptions regarding the error terms and their distribution that often cannot be interpreted economically. Therefore, these models have often been criticized (Ashenfelter und Card 1985). However, Heckman und Hotz (1989) point out that the application of parametric models leads to satisfying results.
- Parametric instrument variable estimators which have increasingly gained attention in recent years may be seen as variant of parametric selection models (Angrist et al. 1996).

All these approaches have their advantages and disadvantages and there are currently no guidelines when to use statistical matching or econometric evaluation models. "[...] Thus the choice of an appropriate econometric model critically depends on the data on which it is applied" (Heckman et al. 1996). Moreover, Heckman und Hotz (1989) conclude that "[...] there is no objective way to choose among alternative nonexperimental estimators." We finally apply a matching approach since the data set has comprehensive information on the firms, thus enabling us to find a "perfect twin", i.e. a similar control observation for every subsidized firm in the upcoming matching process. Moreover, Hausman (2001) states that matching approaches lead to more robust estimates of the treatment effect compared to other methods.

5 EMPIRICAL ANALYSIS

5.1 Initial Situation and Probit Estimation

5.1.1 Pre–match Situation

The data set contains 625 firms (N^1) that received public R&D subsidies. Moreover, there are 303 firms (N^0) that did not receive any public R&D subsidies. Table 1 shows that there are significant differences in the means of several characteristics between both groups (see columns 2 and 3). This indicates that the group of firms that received public R&D subsidies is a selective one. The decision of the firm to apply for public assistance as well as the selection mechanisms on the part of the authorities which distribute the means generate a group of firms with special characteristics. Therefore, a comparison of the firm specific R&D intensities using the initial data set would lead to biased results due to the differences between both groups.

5.1.2 Specification Tests and Probit Estimation

The best and easiest way to find a counterpart for every firm that received public R&D subsidies is to select the non–subsidized one with exactly the same values in the selected matching variables (see Table 1), i.e. a perfect twin. But the relatively large number of these variables and the availability of only about 300 firms in the potential control group impedes this approach. Matching methods which recently became popular in labor market evaluation studies represent a powerful alternative avoiding these difficulties (Lechner 1998). Rosenbaum and Rubin (1983) point out that matching "[...] is a method for selecting units from a large reservoir of potential comparisons to produce a comparison group of modest size in which the distribution of covariates is similar to the distribution in the treated group."

The matching algorithm used corresponds closely to the one applied by Lechner (1998). To reduce the multidimensional problem arising from the relatively large number of covariates to a one–dimensional, initially a probit model is estimated. The decision whether the firm has received public assistance ($S_i = 1$) or not ($S_i = 0$) serves as the endogenous variable:

$$E[S_i|X = x_i] = Pr(S_i = 1|X = x_i) = \Phi(x_i'\beta) \quad \forall \; i = 1, \ldots, N^0 + N^1 \quad (6)$$

Table 1: Mean Comparisons of subsidised firms, firms from the potential control group without subsidisation and the selected control groups

	subsidized firms	non-subsidized[a] firms	selected control[b] firms
industry 1	0.053	0.142*	0.053
industry 2	0.061	0.056	0.061
industry 3	0.023	0.066*	0.023
industry 4	0.084	0.066	0.084
industry 5	0.068	0.089	0.068
industry 6	0.058	0.086	0.058
industry 7	0.143	0.214*	0.143
industry 8	0.214	0.073*	0.214
industry 9	0.122	0.046*	0.122
industry 10	0.093	0.059	0.093
industry 11	0.042	0.056	0.042
industry 12	0.040	0.046	0.040
cohort dummy 1994	0.320	0.558*	0.342
cohort dummy 1996	0.350	0.300	0.341
cohort dummy 1998	0.330	0.142*	0.317
number of employees	191.8	136.3	178.6
export ratio	0.171	0.099*	0.174
market share	0.385	0.278	0.350
import ratio	0.209	0.180*	0.209
sellers concentration (CR6)	0.185	0.169	0.186
West German parent company	0.196	0.191	0.220
foreign parent company	0.048	0.076	0.056
firm age	5.963	7.376	6.564
capital intensity	0.095	0.104	0.097
legal form	0.058	0.092	0.069
R&D department	0.603	0.248*	0.592
propensity score	0.817	0.044*	0.801
observations	622	303	622
different control observations	/	/	157

Notes: * indicates that the means differ with statistical significance in a two–tailed t–test at the 5% level between the supported firms (column 2) and either firms from the potential control group (column 3) or from the selected control group (columns 4).
[a] Non–subsidised firms of the initial sample, i.e. prior to the matching procedure.
[b] Selected non–subsidised firms, i.e. based on the matching procedure.

The vector x_i contains the set of characteristics that potentially influence the probability of receiving public R&D subsidies. These have been introduced in section 3. $\Phi(\bullet)$ is the cumulative density function of the standard normal and β is the parameter vector to be estimated. N^1 and N^0 define the number of assisted and non–assisted firms, respectively.

Tests on normality and heteroscedasticity have been carried out to find potential misspecifications since these would lead to inconsistent probit estimates. We use Lagrange multiplier (LM) tests to check if misspecifications of the distributional assumptions (non–normality, heteroscedasticity) exist (cf. Verbeek 2000). The results of the heteroscedasticity tests are given in Table 2. The statistics are χ^2 distributed with as many degrees of freedom as variables to be tested for heteroscedasticity. The tests do not reject the null hypothesis that error terms are homoscedastic at the 5% level of significance. Moreover, the normality assumption cannot be rejected at the 5% level of significance in a χ^2 test with 2 degrees of freedom (see in Table 2). This test examines whether skewness and kurtosis are characteristic of a normal distribution.

Table 2: Heteroscedasticity and normality tests

variable	degrees of freedom	statistic	prob–value
industry dummies	11	13.290	0.275
cohort dummies	2	4.245	0.120
size groups	5	5.050	0.410
export ratio	1	0.900	0.343
market share	1	0.015	0.903
import ratio	1	0.177	0.674
sellers concentration	1	0.070	0.791
parent company	2	1.096	0.578
1/age	1	0.471	0.492
capital intensity	1	0.213	0.644
legal form	1	0.000	0.984
R&D department	1	2.005	0.157
normality	2	4.941	0.085
number of observations		925	

Hence, no indication of potential misspecification of the homoscedastic probit model are found. Thus, the results can be used for making inferences and the upcoming matching process. Table 3 contains the estimated parameters which will be interpreted briefly at first. In addition to the estimated parameters the table contains the marginal effects which are normally used to interpret the results. Here, the effect of marginal changes of an exogenous variable on the probability to receive subsidies can be examined. The marginal effects for the probit model are calculated according to Greene (2000) in the following way:

$$\frac{\partial E[S|\ X = x]}{\partial x_k} = \frac{\partial Pr(S = 1|\ X = x)}{\partial x_k} = \frac{\partial \Phi(x'\beta)}{\partial x_k} = \phi(x'\beta)\beta_k\ . \tag{7}$$

In equation (7) $\phi(\bullet)$ is the probability density function of the standard normal.

In the probit estimation, several industry dummies, the cohort dummies, the firm size as well as the fact that the potential parent company is located abroad have a significant influence on the probability to receive public R&D subsidies. Moreover, the sellers concentration as well as the existence of an R&D department significantly determine the probability of being subsidized. No a priori considerations were made regarding the influence of the industry dummies. But it turns out that industries that are rather technology intensive (industries 4, 8 to 11) have ceteris paribus a higher probability to receive subsidies. The cohort dummies indicate that in subsidization periods 1996 and 1998 firms had a higher probability to receive subsidies compared to the reference period 1994. The effects amount other things equal to about 20 and 25 percentage points. The existence of a foreign parent company is connected with a decrease of the probability to receive public R&D subsidies c.p. by about 26 percentage points. This indicates that German firms without foreign links are the main focus of public support. The insignificant influence of a West German parent company further supports this finding.

Firm size is a further determinant that significantly influences the subsidisation probability. The larger the firm the better its chances to receive public funds. This is mainly due to information advantages, better capacities to carry out R&D as well as the existence of more staff and capacity to apply for the funds. According to the marginal effects an increase of the firm size by 10% would raise the probability to receive subsidies by about 2.2 percentage points. An existing R&D department has not surprisingly a significant positive effect on the probability to receive subsidies. The existence raises

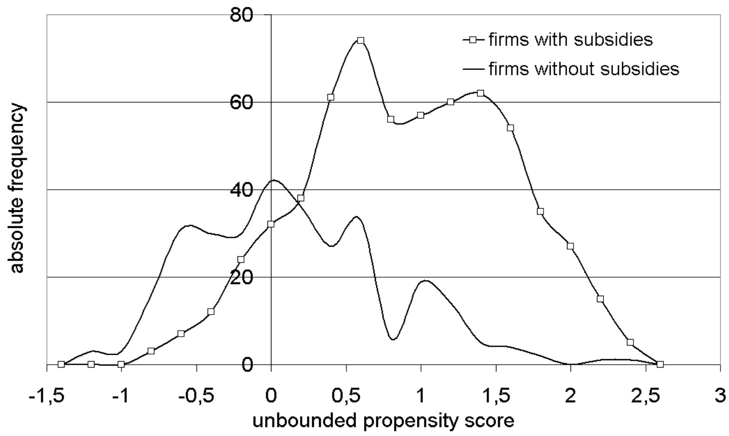
Table 3: Results of the probit estimation

variable	coefficient	t-value	marg. eff.$^{a)}$	t-value
industry 2	0.242	0.620	0.077	0.660
industry 3	0.242	0.860	0.077	0.930
industry 4	1.015	3.110*	0.247	4.940*
industry 5	0.450	1.920	0.135	2.240*
industry 6	0.324	1.390	0.101	1.540
industry 7	0.355	1.850	0.112	2.010*
industry 8	0.880	3.920*	0.241	5.080*
industry 9	1.582	4.010*	0.318	8.480*
industry 10	0.723	2.850*	0.197	3.760*
industry 11	1.095	2.330*	0.250	4.280*
industry 12	0.038	0.130	0.013	0.130
cohort 1996	0.621	5.420*	0.196	5.880*
cohort 1998	0.850	6.190*	0.251	7.420*
ln(employees)	0.641	2.580*	0.218	2.580*
ln(employees)^2	-0.051	-1.830	-0.017	-1.820
capital intensity	-0.196	-0.450	-0.067	-0.450
1/age	0.618	1.170	0.210	1.170
West German parent company	-0.223	-1.680	-0.079	-1.630
foreign parent company	-0.680	-3.280*	-0.258	-3.160*
export ratio	0.004	1.550	0.001	1.550
import ratio	0.011	1.160	0.004	1.160
sellers concentration	-0.022	-2.970*	-0.008	-2.970*
market share	-0.006	-0.210	-0.002	-0.210
R&D department	0.681	6.300*	0.228	6.580*
legal form	0.122	0.640	0.040	0.660
intercept	-2.459	-4.140*	/	/
Pseudo R^2		0.202		
observations		925		

Notes: * indicates statistical significance at the 5% level.
$^{a)}$ $\partial S/\partial x$ is for dummy variables the discrete change from 0 to 1.
The marginal effects will be calculated at the means of the variables.

the probability by about 23 percentage points. Finally, the legal form does not influence the probability to receive subsidies.

After estimation of equation (6) the unbounded propensity score $x_i'\hat{\beta}$ is calculated for every observation. This measure is used in the procedure to find the counterparts for every subsidized firm. We prefer the unbounded rather



Note: Scores ($x_i'\hat{\beta}$) based on the probit model.

Figure 1: Frequency distribution of the unbounded propensity scores of the initial data set

than the bounded propensity scores $\Phi(x_i'\hat{\beta})$ because it has preferable distribution properties (Hujer et al. 1997). We also used $\Phi(x_i'\hat{\beta})$ as matching criterion but there were only marginal changes in the results of the following matching process. Figure 1 shows frequency distributions of the unbounded propensity scores $x_i'\hat{\beta}$ of both firm groups for the initial data set. They fulfill an important assumption for the matching process, since both graphs overlap to a great extent, hence indicating similar distributions of the two groups (Lechner 1998).

5.2 Non–parametric Matching

The general matching process applied proceeds as follows :

1. Separate the observations with respect to their status of public R&D subsidy receipt.

2. Select a firm i that received public R&D funds.

3. Take the unbounded propensity score $x'\hat{\beta}$. In many empirical studies one wants to balance the participiants 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 (cf. Lechner 1998).

4. Then one calculates a proper measure of metric distance, e.g. the Mahalanobis distance. Let:

$$d_{ij} = (x_i'\hat{\beta},\ \nu_i)\,' - (x_j'\hat{\beta},\ \nu_j)\,' \quad \forall\ j = 1, \ldots, N^0$$

for every combination of the R&D recipient i and every firm from the potential control group j. Then calculate the Mahalanobis distance:

$$MD_{ij} = d_{ij}\,'\, Cov^{-1}\, d_{ij} \quad \forall\ j = 1, \ldots, N^0$$

to find the nearest neighbour. Cov 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 some restrictions on the neighborhood:

   - A required criterium to be a neighbor of participant i may be that a potential control firm is recorded in the same industry classification.
   - One shortcoming of the nearest neighbor matching so far is that always a neighbor is picked, even if the metric distance to the i–th control observation is very large. To prevent too large distances, it is possible to define a confidence interval of the propensity score and other matching variables on basis of the participant group in which a potential control observation should be included. This is called calipre matching and was indroduced by Cochran and Rubin (1973). Hujer et al. (1997) give an example for this method.

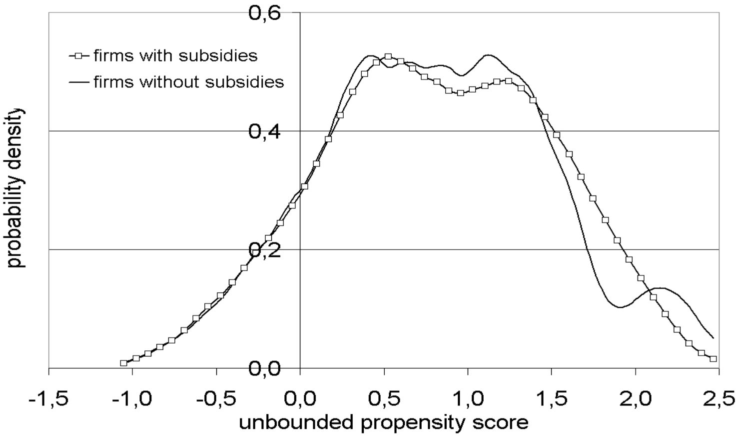
6. The firm j from the potential control group with the smallest Mahalanobis distance serves as control observation in the following success analysis. The comparison observation is drawn randomly if more than one firm attains the minimum Mahalanobis distance. If no potential control observation remains in the pool after applying the restrictions described in the previous step, firm i is bypassed and no match can be made.

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 small number of control firms. Using different data, i.e. a large potential control group, one could also draw without replacement. In this case, it would be important to draw the participants one after the other randomly from the treatment group.

8. Repeat steps 2 up to 7 to find matched pairs for all recipients.

Following matching technique is applied in this paper: We only use the propensity score and impose the restriction that potential controls have to be recorded in the same industry classifications as the participants. If the matching results are not satisfactory, one would proceed with additional variables in the matching function. However, it turned out that using the unbounded propensity score as only matching criterion is already sufficient. Table 1 measures the statistical "similarity" of the observations that remain after the matching procedure. Column 2 contains the means of the variables of the firms with R&D subsidies and columns 4 the means of the assigned firms without such subsidies. Matching is regarded as successful if the means of the relevant variables in both groups do not differ significantly. Note that we found for every participant a neighbor within the confidence interval defined by the calipre restriction with regard to the propensity score. As indicated by a t–test, the differences of the means are small and not statistically significant at the 5% level for all variables. Moreover, the unbounded propensity score $x_i'\hat{\beta}$ as a summary measure of various variables does not significantly differ between both groups, indicating a good fit of the matching algorithm applied. 157 out of the 303 potential control observations are used for the selected control group. This means that each selected control group observation is on average assigned to four subsidized firms.

Figure 2 contains kernel density estimates of the unbounded propensity scores $x_i'\hat{\beta}$ for both groups. The Epanechnikov kernel density estimates instead of histograms serve as tool to show the similarity in the relative frequencies (probability density) since both groups contain the same number of observations after the matching process (c.f. Silverman 1986). The are nearly no differences on the left and the middle part of the distribution. Due to the small number of non–subsidized firms on the right tail (see Figure 1)



Note: Scores $(x_i'\hat{\beta})$ based on the probit model.

Figure 2: Density distribution of the unbounded propensity scores after the matching process

it is difficult to find adequate matches pairs. All in all, the figure underlines the quality of the matching procedure.

6 CAUSAL EFFECTS

The success of public R&D subsidies is evaluated by comparing the average firm specific R&D intensities between the groups of subsidized and non–subsidized firms, i.e. Y_i^1 and Y_i^0. The unbiased estimator for the causal effect $\hat{\theta}^1$ is the difference of the means between both groups

$$\hat{\theta}^1 = \frac{1}{N^1}\left(\sum_{i=1}^{N^1} Y_i^1 - \sum_{i=1}^{N^1} Y_i^0\right). \tag{8}$$

R&D subsidy programs have on average a positive impact on the firm specific R&D intensity if the causal effect $\hat{\theta}^1$ is significantly greater than zero. The programs do not generate positive effects if $\hat{\theta}^1$ is statistically insignificant. Finally, subsidized firms perform worse than firms without subsidies if the causal effect is significantly smaller than zero. This means that non–subsidized firms undertake on average more R&D efforts (measured with the R&D intensity) than firms that received funding within the programs under evaluation.

The test on the effect is usually carried out by means of a simple t–statistic. In this case, however, the ordinary t–value is biased upwards because it does not take into account that the mean of the outcome variable of the control group is not a result of a random sampling but an estimation: it is based on the estimated propensity scores and the non-parametric matching procedure. Thus, the usual t–statistic may be misleading for making inferences. To remove the bias of the t–statistic, the method of bootstrapping is applied, i.e. we simulate the distribution of the mean outcome of the control group by repeated sampling (for a sketch of bootstrapping, see Greene 2000 or Efron and Tibshirani 1993 for a comprehensive discussion):

- A random sample with replacement is drawn from the original sample, which has the same size as the original one.
- Afterwards, we estimate the probit model again and perform a new matching with this sample and record the mean difference $\hat{\theta}^1$ after the procedure.
- The whole process is repeated 200 times.
- Subsequently, we receive a simulated distribution of mean differences between the participants and their controls. This empirical distribution can subsequently be used to calculate a standard error and, thus, an unbiased t–statistic.

Applying equation (8) leads to an average R&D intensity of about 6.6 (2.6) % for the subsidized (non–subsidized) firms. Thus, the resulting causal effect amounts to about four percentage points. According to the result of the two tailed t–test, this effect is statistically significant different from zero, even according to the bootstrapping. As mentioned above, the result shows that the ordinary t–statistic is biased downwards.

Eastern German firms which receive public R&D funds achieve on average higher firm specific R&D intensities compared to firms that do not receive public R&D support, given that the firms from both groups do not differ with respect to exogenous variables that influence the probability of receiving public R&D subsidies. The results confirm that public R&D schemes

Table 4: Causal effect — firm specific R&D–intensity

firms	subsidized firms $\hat{E}[Y^1 \mid S=1]$ (per cent)	non–subsidized firms $\hat{E}[Y^0 \mid S=0]$ (per cent)	causal effect $\hat{\theta}^1$ (percentage points)	test statistic t–value (bootstrap t–value)
622	6.57	2.63	3.94	8.24* (5.32*)

Note: * indicates statistical significance in a two–tailed t–test at the 1% level.

in Eastern Germany are an important factor for stimulating private R&D efforts.

The significantly higher R&D intensities for subsidized firms indicate that complete substitution of public means does not take place, i.e. the absence of perfect crowding–out. The recipients increase instead their private R&D efforts in the case of public subsidization. This is especially important in a transition economy like Eastern Germany, where private R&D is indispensable for creating innovative and viable economic structures after more than 40 years of a planned economy.

Of course, it be would interesting to know how large the net effect of public funding is for the Eastern German manufacturing sector at all. The MIP provides weights for its sampled firms which allow to calculate population weighted descriptive statistics and, in our case, to estimate a macroeconomic effect roughly. According to these information, the total R&D expenditure in the Eastern German manufacturing sector in 1998 was about 3.84 billion DM. Firms that participated in any public innovation scheme spent almost 3.4 billion DM of this amount. According to the result displayed in Table 4, we assume that 60% of recipients' R&D activities are on average due to public funding. Applying this rule of thumb, we derive a macroeconomic effect of 2.04 billion DM according to subsidies. This effect is large compared to other studies cited in section 2. However, keeping in mind that the transformation process in Eastern Germany is heavily fostered by the government, this figure seems to be plausible. Of course, it would be desirable to carry out a cost benefit analysis, but unfortunately the German Federal Government does not provide any information on how the 2 billion DM of public funding dedicated to the business sector (BMBF 2000) are allocated to Eastern and Western German firms.

7 CONCLUSIONS

This papers provides new evidence to the discussion on whether public R&D funds crowd out private investment in innovations. It is analyzed whether the participation in public R&D programs leads on average to a higher R&D intensity at the firm level. Using a non–parametric matching approach, we compare the potential outcome of this group to a matched control group of non–subsidized firms.

The analysis has some advantages over previous studies. The information collected in the Mannheim Innovation Panel is not restricted to a particular measure but covers all public funding activities by the EU, the federal government and the federal states in the years after reunification. However, it is not possible to track in which program a firm participated with the available information. The procedure used to identify the causal effect of public R&D schemes is also new to this kind of literature. We use a non–parametric matching approach to define a suitable control group.

The study comes up with following results: the causal effect identified is significantly positively different from zero, i.e. firms that received public funding achieve on average a higher R&D intensity than firms belonging to the selected control group. The causal effect amounts to about four percentage points on average. For example, a subsidized firm with a turnover of 100,000 monetary units would on average have invested 4,000 monetary units less if it did not participate in public R&D schemes.

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APPENDIX: INDUSTRIES IN SAMPLE

Table 5: Classification of Industry Dummies

Industry Dummy	Description
industry 1	Food and beverages
industry 2	Textiles, clothes and leather goods
industry 3	Wood, paper, publishing and printing
industry 4	Fuels and chemicals
industry 5	Rubber and plastic products
industry 6	Non–metallic mineral products
industry 7	Basic and fabricated metals
industry 8	Machinery and equipment
industry 9	Office and communication equipment, electrical machinery and components
industry 10	Medical and optical instruments
industry 11	Motor vehicles and other transport equipment
industry 12	Furniture products and n.e.c.