R&D subsidies to small young companies: should the independent and high-tech ones be favored in the granting process?

Dirk Czarnitzki[a] and Julie Delanote[b]

a) K.U.Leuven, Dept. of Managerial Economics, Strategy and Innovation, Belgium; Center for R&D Monitoring (ECOOM) at K.U.Leuven and ZEW Mannheim, Germany
b) K.U.Leuven, Dept. of Managerial Economics, Strategy and Innovation, Belgium; Center for R&D Monitoring (ECOOM) at K.U.Leuven and ZEW Mannheim, Germany

(julie.delanote@econ.kuleuven.be)

Abstract

R&D activities of small and young firms get increasing attention from both scholars and policy makers due to the expectations on the creation of valuable new knowledge. As a consequence, small young firms are considered as important actors in the flagship initiative 'Innovative Union' of the 'Europe 2020' targets and an important number of R&D subsidies are targeted towards these firms. However, it remains unclear whether all small young firms make efficient of this support. While governments already actively target young, small independent firms and increasingly acknowledge the importance of sectoral differentiation, there is no decisive evaluation yet on the importance of letting these factors have an influence on subsidy receipt of small young firms. Therefore, we compare the effect of innovation subsidies on independent high-tech small young firms (NTBFs), independent low-tech small young firms (LTBFs) and their group counterparts. Based on caliper matching, this study reveals that full crowding-out with regard to public funding can be rejected for all firm types studied. In addition, this study assesses the difference in treatment effects of the different firm types in a regression framework. The results reveal that a focus on independent firms is only efficient if the target group is restricted to high-tech firms. The only firms that convincingly make more efficient use of subsidies than the other small young firms, both in terms of R&D expenditures and in terms of R&D employment, are NTBFs.

Keywords: innovation subsidies, NTBFs, policy evaluation, treatment effects

1 Introduction

Business R&D efforts have been widely acknowledged as being essential for technological change and growth (Romer, 1990). Multiple empirical studies have provided evidence for this beneficial effect of innovation (Mansfield, 1988, 1962; Aghion and Howitt, 1998; Scherer, 1965; Geroski and Toker, 1996). Expectations on the creation of valuable new knowledge are especially high for small and young firms. The first scholar explicitly pointing to the importance of innovative, small young firms is Schumpeter. Schumpeter's Mark I scenario describes the technological importance of new entrants that are involved in innovation activities. Following Schumpeter, the innovation activities of young and/or small firms gained increasing attention from both scholars and policy makers (Colombo and Grilli, 2006; Veugelers, 2008; Colombo and Grilli, 2010; Schneider and Veugelers, 2010). Apart from their potential direct contribution to economic growth, innovative youngsters are in the focus of interest because of their expected indirect positive effects on large incumbent firms and their ability to create new markets.

Before introducing an innovation on the market, these small young firms need to invest in R&D. However, investment in R&D suffers from market failures. First, firms might be reluctant to invest in R&D as the generated knowhow by R&D activities can spillover to competitors, hindering the appropriation of the returns from the initial investment (Schumpeter, 1942; Nelson, 1959; Arrow, 1962). In addition, innovative firms often face financial constraints for R&D activities. Funding R&D projects is risky, as the outcome of R&D investments is often very unclear and once the R&D investment is effectuated, it is irreversible, no matter what the outcome is (Pindyck, 1991; Dixit and Pindyck, 1994). Indeed, R&D investments encompass a large share of sunk costs. Not only equipment can be highly project-specific, but also the human capital and the tacit knowledge that this entails. These specific characteristics of R&D investments lead to information asymmetries between firms and external suppliers of finance, resulting in underinvestment in R&D (Arrow, 1962; Stiglitz and Weiss, 1981). These problems are worse for young and small firms than for larger and more mature firms as they usually lack the experience and necessary relationships that could reduce problems of asymmetric information (see Himmelberg and Petersen, 1994; Czarnitzki and Hottenrott, 2011 and Hall and Lerner, 2010 for a recent survey).

As a consequence of these information asymmetries, internal finance turns out to be an important determinant of R&D investment. Ever since Schumpeter, who emphasized the necessity of temporary monopoly profit for financing of future R&D, economists acknowledged the importance of internal finance for funding R&D investment and further elaborated upon this topic (Schumpeter, 1942). Several scholars found a positive relationship between R&D investment and internal finance for small and/our young firms (Himmelberg and Petersen, 1994; Czarnitzki and Hottenrott, 2011). However, as pointed out by these scholars, especially small young firms have limited access to internal funds as they cannot use earlier profit accumulations or a steady cash inflow from a broad and established product portfolio for financing their R&D projects.

The different constraints to R&D investment described above cause the retention of investing in certain R&D projects, especially by small young firms. Consequently, several R&D projects that would lead to high social returns are not undertaken as the private returns are considered as too low and/or too uncertain. The optimal social level of investment is thus higher than the actual, suboptimal level of private investment. In order to align the private and optimal social level of investment, governments typically subsidize R&D and innovation activities. Policy makers in Europe did not remain indifferent to the specific constraints faced by small young firms and the presumed beneficial effect of subsidies. As a consequence, they are heavily engaged in providing support for innovation activities of this type of firms. The increased attention towards small and young firms fits within the flagship initiative 'Innovation Union' under the 'Europe 2020' targets, the reworked Lisbon Strategy 2010 goals (EC-DG Research and Innovation, 2011).

One of the main objectives of the European Commission is to provide 'less and better' general state aid. The recent developments show that state aid is effectively declining relative to GDP. Nevertheless, the state aid for research, development and innovation continues to increase (EC-DG Research and Innovation, 2011). However, this should not be considered as a positive evolution, just like that. It should not be the aim to solely give more state aid for research, development and innovation in general, but to efficiently spend the resources. Indeed, the additional fundings should be first provided to the companies being most in need of them and most efficiently using these funds. Moncada et al. (2010) states that at least size, age, innovativeness and sectoral differentiation should play an important role in the choice of policy measure targets. He claims that the granting process of innovation subsidies should be oriented towards small, young, high-tech innovators. In addition, the European Commission specifies that aid to small companies should be limited to small firms that are also independent, thus not part of a group. The rationale behind this is that group firms have the advantage of their parent and are not in the highest need of subsidies. The non-group counterparts on the other hand, lack the critical mass and the experience to access funds for their high-risk R&D projects.

Table 1: Overview of the firms studied, embedded in the full sample

<table>
<tr><td>NTBF
Small, young independent firms, active in high-tech sectors</td><td>Group NTBF
Small, young group firms, active in high-tech sectors</td><td rowspan="2">Small Old firms</td></tr>
<tr><td>LTBF
Small, young independent firms, active in low-tech sectors</td><td>Group LTBF
Small, young group firms, active in low-tech sectors</td></tr>
<tr><td colspan="2">Large young firms</td><td>Large old firms</td></tr>
</table>

In order to evaluate whether the subsidy granting process of small young firms should be determined by independence and sectoral differentiation, we compare the impact of subsidies on small young firms that are either independent or part of a group and active in high-tech or low-tech sectors. In order to do so, we analyze the subsidy impact on New Technology Based Firms (NTBF), group NTBFs, Low Technology Based Firms (LTBF) and group LTBFs. NTBFs are, since their introduction by the Arthur D. Little Consulting Group a well-known type of firms (Little, 1977). Several scholars investigated this type of firms and found, in general, a high innovative performance and growth

(Storey and Tether, 1998; Colombo and Grilli, 2010; Licht and Nerlinger, 1998; Almus and Nerlinger, 1999). While some scholars deviate from the original definition of NTBFs, we stay close to how the concept was initially defined by Little (1977). In this study, NTBFs refer to small, young, independent firms active in high-tech sectors. LTBF is a concept coined by us in order to denote the 'counterparts' of NTBFs with respect to sector of activity. While NTBFs are active in high-tech sectors, LTBFs are small, young indepedendent firms active in low-tech sectors. We also evaluate the subsidy impact on LTBFs and NTBFs that are not independent, but part of a group, in order to assess the relevance of current policies to mainly target independent firms. Figure 1 graphically presents the four groups of firms analyzed in this study and recapitulates the differences between the different types of firms.

We evaluate the impact of direct R&D subsidies granted to companies on R&D input, both at the European and the national level. As already explained above, with these public subsidies, the government attempts to jazz the innovation activities to the social optimal level, as much as possible. In order to correctly evaluate the impact of subsidies on the R&D investment of New Technology Based Firms, we perform caliper matching.

The remainder of the paper is organized as follows: section 2 reviews the evaluation literature and outlines the econometric method used, section 3 discusses the data used and presents descriptive statistics and section 4 presents the empirical results. Finally, a concluding section summarizes the findings and discusses policy implications.

2 Subsidy evaluation

In this study, we evaluate the impact of direct subsidies on innovation input. It is not always clear how firms that receive these subsidies react to this support. Indeed, it is possible that the subsidies are completely inefficiently spent if no extra R&D is undertaken. This might happen if firms simply replace their privately sponsored R&D projects by the publicly subsidized ones. This phenomenon is denoted as crowding-out, and refers to the situation in which innovation projects are subsidized that would also have been carried out without public subsidies. Of course, it is not the aim to redirect all innovation subsidies to firms that do not make efficient use of these subsidies. If we would find, for example, that LTBFs make efficiently use of subsidies, while the NTBFs do not, a redirection of all innovation subsidies towards high-tech firms would go against the goals of the EU to give 'less and better' state aid. Similarly, most innovation subsidies to young small firms are oriented towards firms that are not part of a group. However, if our results would reveal a more efficient use of innovation subsidies by group NTBFs and LTBFs, this points to a current wrong focus of funding.

In order to measure the effect of public support on R&D input, several econometric models were proposed. However, estimating the effect of public subsidies is not that straightforward as subsidies are likely to be endogenous. Indeed, firms that receive a subsidy are presumably different from companies that do not receive a subsidy. A first difference already emerges at the application stage as some firms might be more likely to apply for public funding than others. Indeed, some firms might consider the administrative burden or the information sharing conditional upon being subsidized as important reasons to restrain from applying for a subsidy. In addition, there is a possibility that the funding agencies follow a picking-the winner strategy with respect to the firms that applied for a subsidy. In other words, firms might have some characteristics that make them more attractive to governments for funding. As a consequence, funding cannot be considered as a random process and this selection should be accounted for when evaluating subsidies. Indeed, comparing the subsidized and unsubsidized firms based on random samples would lead to biased results. In order to correctly evaluate the impact of subsidies on the R&D investment of the different firm types, matching is performed in this study.

literature

The impact of R&D policies on firms' innovation behavior has already been extensively covered in the economic literature. The main focus in literature, as well in this paper, is on the input additionality of subsidies. As a consequence, most of the literature addressed the issue of crowding-out effects of subsidized R&D. David et al. (2000) and Cerulli (2010) survey the literature on subsidy effects and find that, in general, the results of the reviewed literature vary a lot and only a limited number of authors effectively tackles the selection bias described above.

Busom (2000), for example, applied a selection model and excluded total crowding-out. Lach (2002) and Gonzales et al. (2005) reject total crowding-out by analyzing the effect of subsidies using Difference-in-Differences and simultaneous equation models with threshold, respectively. A lot of studies applied matching, the method that is also used in this paper, in order to evaluate the effect of R&D subsidies. Almus and Czarnitzki (2003), for example, reject crowding out as they find that Eastern German firms that received public R&D subsidies increased their innovation activities.

Similarly, Aerts and Czarnitzki (2004), Duguet (2004); Czarnitzki and Hussinger (2004) and Gonzales and Pazo (2008) find no proof of crowding out in respectively Belgium, France, Germany and Spain. Czarnitzki and Lopes Bento (2010) apply matching in a cross-country comparative evaluation and also reject total crowding out.

In line with policy attention, several scholars shifted their attention towards subsets of firms, by focusing on younger and/or smaller firms when evaluating the effect of public subsidies on R&D input. Wallsten (2000), for example, uses a 3SLS approach in order to evaluate the effect of grants to small firms in the context of the SBIR program. At first sight, he finds proof of crowding-out of firm-financed R&D spending dollar for dollar. However, Wallsten (2000) correctly remarks that this result could be simply due to the fact that firms would have cutted back their R&D expenditures in case no public funding was available. In other words, the R&D grants may have allowed firms to continue their R&D at a constant level rather than cutting it back. Reinkowski et al. (2010) apply matching in their paper and specifically focus on SMEs. They find that SMEs, and especially the micro firms show an increase in R&D intensity as a result of the subsidies. Reinkowski et al. (2010) also find that subsidies increase the probability of patent application for small and medium sized firms.

While the above studies already focus on subsets of firms, the impact of subsidies on the group of NTBFs and its counterparts has not been discussed extensively in the literature so far. Some studies evaluated the effect of subsidies on output measures. Colombo et al. (2008) for example show, by applying an augmented GMM estimator, that NTBFs grow most after receiving public funds and especially if these are allocated through a selective evaluation process. Colombo et al. (2011) and Grilli and Murtinu (2012) focus more specifically on R&D subsidies and find that TFP growth of NTBFs is only enhanced if subsidies are provided competitively and if they aim at enhancing R&D investments. Just like Colombo et al. (2008), they evaluated subsidy impact by applying an augmented GMM estimator.

Apart from the current study, there are, to our knowledge, no papers that study the effect of innovation subsidies on R&D input of NTBFs. In addition, there are no studies that investigate the different subsidy effects on NTBFs, Group NTBFs, LTBFs and Group LTBFs, evaluating that way whether the current policy focus towards non-group firms in high-tech sectors is really as fruitful as presumed.

matching

Several econometric evaluation techniques have been developed in order to correct for the selection bias in identifying treatment effects. As participants in the granting process of public measures often differ from non-participants in important characteristics, the literature on the econometrics of evaluation offers different estimation strategies in order to correctly evaluate policy measures (see Heckman et al., 1999 and Imbens and Wooldridge, 2009 for surveys). Some of the methods that could be used to tackle the selection problem are the difference-in-difference estimator for panel data and the selection model, the instrumental variables estimator and non-parametric matching for cross-sectional data (see Cerulli, 2010 for a recent survey on this topic). The difference-in-difference method for panel data cannot be used with our data as we are working with cross-sectional data (see below). Indeed, the difference-in-difference method requires panel data with observations before and after/while the treatment. Estimating IV and selection models could be considered in order to correctly estimate the subsidy-effect in the context of cross-sectional data. However, none of these methods is fully satisfactory as finding the correct instrumental variables or exclusion restriction is a pretty cumbersome task. Indeed, it is almost impossible to find variables that can really be interpreted as exogenous to the treatment. Another possibility is to perform matching. This estimation method has the advantage over the other techniques that it is not necessary to specify a functional form and that there is no need for a distributional assumption on the error terms of the selection and outcome equations. A disadvantage is that matching only controls for observed heterogeneity between treated and untreated firms. In other words, matching does not control for unobserved factors that could influence the subsidy granting process. An effective tool that controls for both selection on observables and unobservables constant over time is the conditional difference-in-difference method, a combination of matching and the difference-in-difference method. However, panel data is required in order to use this mixed method and this estimation technique is thus unusable for our data. Nevertheless, the large scope of the set of covariates included in our estimations allows us to assume that selection on unobservables is not a problem in this paper.

The technique of matching has, among others, been discussed by Angrist (1998); Dehejia and Wahba (1999); Heckman et al. (1997); Heckman, Ichimura and Todd (1998); Heckman, Ichimura, Smith and Todd (1998) and Lechner (1999, 2000). In the context of this paper, matching addresses the following question: "What would a subsidized firm with given characteristics have done if it had not been subsidized?". In general, we want to observe the difference between the actual observed

R&D expenditures of the subsidized firms and the counterfactual situation. The average treatment effect α_{TT} of firms receiving a subsidy (T) relative to firms receiving no treatment (C) can be written as:

$$E\left(\alpha_{\mathrm{TT}}\right) = \mathrm{E}\left(\mathrm{Y}^{\mathrm{T}}|\mathrm{S}=1\right) - \mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}|\mathrm{S}=1\right) \tag{1}$$

In this equation, Y^T denotes the outcome of the treated firms and Y^C the outcome of the untreated firms. S takes the value 1 if the firm is subsidized and zero otherwise. However, it is impossible to observe Y^C in the counterfactual situation as it is impossible to observe the actual behavior of the same firm without treatment. As a consequence, this counterfactual outcome, Y^C, has to be estimated as reliable as possible. This counterfactual outcome of treated firms is constructed from a control group of non-subsidized firms. The idea is to balance the sample of subsidized firms and comparable non-subsidized firms. The remaining differences between the matched firms can then be fully attributed to the received treatment, a subsidy in this case.

It already became clear above that comparing the subsidized and unsubsidized firms based on random samples would lead to biased results because of the possible selection bias. When performing matching, we replicate the conditions of an experiment to the best possible extent. Therefore, we determine a broad set of characteristics, X, that should be equal among the compared firms. In other words, we compare the treated firm with an untreated firm that is identical to the treated firm with respect to the characteristics that we define. This set of characteristics should be exhaustive. Rubin (1977) introduced this as the Conditional Independence Assumption (CIA), which stipulates that the treatment and the outcome of this treatment are independent for the observations having the same set of exogenous characteristics. If this CIA is satisfied, the following equation is valid:

$$\mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}|\mathrm{S}=1,\mathrm{X}\right) = \mathrm{E}\left(\mathrm{Y}^{\mathrm{C}}|\mathrm{S}=0,\mathrm{X}\right) \tag{2}$$

In that case, the outcome of the non-subsidized firms can be used to estimate the counterfactual situation of the subsidized firms. The treatment effect can then be written as:

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

However, although this condition may seem to be very straightforward, it is not trivial to include all relevant characteristics. Nevertheless, the Conditional Independence Assumption is assumed to be satisfied for our dataset as the latter contains a rich set of variables. Based on these appropriate characteristics, X, the selection problem is overcome and the samples of subsidized and unsubsidized firms come close to an experimental setting.

Usually, X contains many different variables in order to satisfy the Conditional Independence Assumption. This makes it almost impossible to find control variables that exactly fit the characteristics of the subsidized firm. In other words, the so-called curse of dimensionality enters because the more dimensions that are included, the more difficult it becomes to find a good match. Rosenbaum and Rubin (1983) showed that it is possible to reduce X to a single index -the propensity score P- and match on this index instead of on all the individual X. Therefore, a probit model is estimated on the dummy indicating the receipt of subsidies. Subsequently, the estimated propensity scores are used as matching argument.

It is necessary that the propensity score of the treatment group and the control group coincide. In some cases, however, this is not the case. This problem is referred to as the 'common support problem'. If the overlap between the different subsamples is too small in terms of the characteristics controlled for, the matching estimator is non-applicable. As a consequence, it is crucial that the sample of unsubsidized firms contains at least one observation similar to each subsidized firm. This requirement is imperative, as, when performing matching, we restrict the sample to firms with common support.

In this study, we evaluate the effect of subsidies with caliper matching (Cochran and Rubin, 1973). This method is similar to nearest neighbor matching method but it adds an additional restriction. In this case, treated units are selected to find their closest match in terms of the propensity score, but only if the propensity score of the control is within a certain, pre-specified, distance. Thus, by applying this method, it is possible that a treated observation cannot be matched to a control. The matching routine used in this paper is presented in table 2. In addition, as an additional restriction, we require the firm observations in the control group to belong to the same year and the same region (Eastern versus Western Germany) as the corresponding firm in the group of subsidized firm observations.

Table 2: The matching protocol

Step 1	Specify and estimate a probit model to obtain the propensity scores $\hat{P}(X)$.
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. (This step is also performed for other covariates that are possibly used in addition to the propensity score as matching arguments.)
Step 3	Choose one observation from the subsample of treated firms and delete it from that pool
Step 4	Find an observation in the sub-sample of subsidized firms that is as close as possible to the one chosen in step 3 in terms of the propensity scores, but only if the propensity score of the control is within a certain, pre-specified, distance. Closeness is based on the Mahalanobis distance between this firm and all non-subsidized firms in order to find the most similar control observation. MD_{ij}=(Z_j-Z_i) Ω^{-1} (Z_j-Z_i) where Ω is the empirical covariance matrix of the matching arguments based on the sample of potential controls. Do not remove the selected controls from the pool of potential controls, so that it can be ued again
Step 5	repeat steps 3 and 4 for all observations on subsidized firms
Step 6	Compute the estimate of the treatment effects using the results of step 5
Step 7	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.

3 Data, variables and descriptive statistics

Data

The data used in this paper stems from the Mannheim Innovation Panel (MIP), the German variant of the Community Innovation Survey. Next to information on general firm-level characteristics, this dataset contains specific information on innovation activities. Indeed, we do not only have information on R&D and innovation expenditures, but we also know whether respondent firms received innovation support from public sources. We use the following MIP waves, dependent upon inclusion of the subsidy receipt question in the survey, in order to evaluate the subsidies granted to NTBFs: MIP1995 (1992-1994), MIP1997 (1994-1996), MIP1999 (1996-1998), MIP2001 (1998-2000), MIP2003 (2000-2002), MIP2004 (2001-2003), MIP2005 (2002-2004) and MIP2007 (2004-2006).

Our sample includes NTBFs, Group NTBFs, LTBFs and Group LTBFs. All these firm classes have less than 250 employees and are less than 10 years old. In addition, all the firms in the sample are innovative and have thus introduced at least one new or significantly improved product or process, or have ongoing or abandoned innovation projects over the period covered in the survey. While NTBFs and LTBFs are not part of a group, their Group counterparts are. NTBFs and Group NTBFs belong to medium high-tech and high-tech sectors, while LTBFs and Group LTBFs belong to medium low-tech and low-tech sectors (for an overview of the industry classification, see table A1 in appendix). Table 3 presents the sizes of the different samples before and after matching. As can be derived from the table, the sample initially consists of 1247 NTBFs, 619 Group NTBFs, 968 LTBFs and 471 Group LTBFs. Each time, a part of the firms are subsidized and a part not. All non-subsidized firms can potentially serve as controls for matching. Table 3 shows that, in line with expectations, a larger share of NTBFs receive subsidies than LTBFs. After matching, the sample of subsidized firms is slightly reduced to 616 subsidized NTBFs, 257 subsidized Group NTBFs, 283 subsidized LTBFs and 97 subsidized Group LTBFs, to which an equal number of non-subsidized firms were matched.

Table 3: The samples further unfolded

<table>
<tr>
<td>NTBF
subsidized 664
potential controls 583
Matched subsidized firms: 616</td>
<td>Group NTBF
subsidized 315
potential controls 304
Matched subsidized firms: 257</td>
<td rowspan="2">Old firms (< 250 employees, ≥ 10 years old)
6432 obs</td>
</tr>
<tr>
<td>LTBF
subsidized 328
potential controls 640
Matched subsidized firms: 283</td>
<td>Group LTBF
subsidized 121
potential controls 350
Matched subsidized firms: 97</td>
</tr>
<tr>
<td colspan="2">Large firms (≥ 250 employees, < 10 years old)
695 obs</td>
<td>Large and Old firms (≥ 250 employees, ≥ 10 years old)
2936 obs</td>
</tr>
</table>

Unfortunately, we can use the data only as pooled cross-sections, but not as a panel. Indeed, of the total initial sample of 3305 observations, corresponding to 2413 individual firms, 72.03% of the individual firms is only observed once in our sample, corresponding to 52.59% of the total number of observations. As a consequence, panel econometric approaches are ruled out as this would significantly reduce the number of observations in our sample. Indeed, over the individual firms, only 0.21% is observed over all the years of the analysis, corresponding to 0.76% of all firm-year observations.

variables

This study investigates the influence of subsidies on various outcome variables. The receipt of subsidies over the covered survey period is denoted by a dummy variable SUB. The subsidy dummy covers subsidies from the national or regional governments and from the EU. In order to evaluate the effect of subsidies on the innovative behavior of firms, we investigate the impact on R&D intensity of these firms, RDint. This variable is constructed as the ratio of internal R&D expenditures to turnover (multiplied by 100). Next to the R&D intensity, we also evaluate the subsidy effect on R&D expenditures (R&D).

A large part of R&D spending consists of salary payments for R&D employment. If companies increase their R&D expenditures after receiving R&D subsidies, a large fraction of these increased spendings might be distributed towards hiring new R&D employees, enlarging that way the inventive capacity. However, as Goolsbee (1998) states, R&D labor supply is quite inelastic and the increased spendings might as well be redirected to higher wages for the existing staff instead of resulting in new human capital which is, off course, not the direct aim of government subsidies. In order to evaluate the impact of innovation subsidies on R&D employment, we investigate the impact of R&D subsidies both on the number of R&D employees (RDemp) and on the R&D employment intensity (RDEint), measured as the number of R&D employees over the total number of employees (multiplied by 100).

Several control variables are included in the analysis that might affect the probability to receive a subsidy as well as the different outcome variables. A first variable that is included is size. Although we are already focusing on small firms, there might still be differences between the larger and smaller firms in this subset. In general, it is posed that larger firms are more eager to innovate. Consequently, even amongst the subset of small firms, we should take the possible differences between firms of different size into account and include size in our propensity score. Firm size is considered, both in its logarithmic form (ln(EMP)) and as a square of this logarithm ($\ln(EMP)^2$) in order to capture possible nonlinearities. Similarly, although we are already focusing on the smallest firms of the economy, we include the logarithm of age (ln(AGE)) in the analysis in order to capture differences between real start-ups and somewhat older firms.

Firms that export to other countries might be more innovative than other companies. The chance that they apply for innovation subsidies is thus also higher. As a consequence, a dummy indicating whether a firm is an exporter or not, EXPORTER, is included in the analysis. Another variable that is assumed to be positively correlated with subsidy receipt is capital intensity (CAPINT). Capital intensive firms supposedly rely more heavily on innovation activities than the less capital intensive ones.

Another variable that is included is price-cost margin (PCM), a good proxy for profits. Firms with a higher price-cost margin are more likely to have financial resources for internal funding of R&D projects, which is positive in light of financial constraints as discussed above. As a consequence, they will apply less for subsidies. On the other hand, their high price-cost margin might be the result of successful past innovation activities and the likelihood to enroll in subsidy programs might thus increase. The price-cost margin is constructed as suggested by Collins and Preston (1969) and Ravenscraft (1983) ((sales - staff cost - material costs)/sales).

The history of (succesful) R&D activities is likely to strongly influence both the probability to receive subsidies, R&D expenditures and R&D employment. If a firm already has a lot of experience in R&D activities, this firm is more likely to know how to apply for subsidies and to invest more in new R&D activities. In addition, governments often adopt a picking-the-winner strategy and firms with previous successful innovations might thus be favored in the granting process. In order to capture the influence of past R&D, we include the patent stock in our regression as patent stock per employee (PS/EMP). We divide by employees in order to reduce potential multicollinearity with firm size. Patent stock is defined as

$$\mathrm{PS}_{it} = (1-\delta)\,\mathrm{PS}_{i,t-1} + \mathrm{PA}_{it},$$

where PS is the patent stock of firm i in period t and t-1 respectively, PA is the number of patent applications filed at the EPO in period t. The patent stock in period t-1 is depreciated at a constant rate, with δ set to 0.15 (see e.g. Jaffe (1986); Hall (1990); Griliches and Mairesse (1984)).

As already elaborated upon above, credit constraints might also have an influence on subsidy receipt and the outcome variables. In order to capture the access a firm has to external capital, we use the firm's credit rating, RATING, lagged one period. The credit rating is obtained from Creditreform which is the largest German rating agency. The rating is an index ranging from 100 to 600, where 600 is the worst and essentially corresponds to bankruptcy of the firm.

The dummy variable EAST indicates firms that are located in Eastern Germany. Eastern Germany is still in transition from a planned to a market economy, and firm behavior may thus be different. In addition, Eastern German firms are preferred in the policy incentive schemes, and special schemes have been launched exclusively for these firms in order to accelerate the catching up process in this region.

In addition, we control for differences in technological opportunities with industry dummies. The complete industry structure for the medium high-tech and high-tech industries on the one hand and the medium low-tech and low-tech industries is presented in table A1 in appendix. These industry dummies are based on the NACE codes, the Statistical Classification of Economic Activities in the European Community. This classification is a European industry standard classification system. Finally, seven time dummies are constructed in order to control for business cycle effects.

For the variables PCM, CAPINT and RATING, we have many missing variables. In order to account for these missing values, we construct dummy variables equal to 1 if the values are missing (D(PCM), D(CAPINT) and D(RATING)). In addition, we set the missing values in the original variables to zero. Including both the dummy variable and the adjusted original variables in the analysis corrects for missing values and prevents the imputation of unknown values. Off all variables that are not constant over time and when possible, the lagged value is included in the estimation. The only variables for which no lagged value is included are AGE and EAST as AGE is truly exogenous and EAST is time-invariant.

Descriptive Statistics

Table 4 displays the descriptive statistics of the variables used in order to evaluate subsidies for the four different firm classes. The t-tests reveal that there are some significant differences between the group of subsidized firms and the potential control group. The subsidized firms are, on average, more export-oriented, are mostly situated in East-Germany and have more patents per employee. Some average differences are only significant for specific firm types. For example, only the independent subsidized firms have, on average, significant more employees than the non-subsidized independent firms. Similarly, only the class of NTBFs has, on average, a significant lower credit rating (thus higher values of the RATING variable) for subsidized firms than for the potential control group.

Table 4: Descriptive statistics[a]

	Strict NTBFs					**Group NTBFs**				
	subsidized firms N_1=664		potential control group N_1=583		p-value of two-sided t-test on mean equality	subsidized firms N_1=315		potential control group N_1=304		p-value of two-sided t-test on mean equality
	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
EMP	42.303	52.521	36.458	48.600	p = 0.042	79.584	71.421	89.895	159.357	p = 0.297
AGE	6.136	2.031	6.202	2.109	p = 0.0.570	6.079	2.080	6.082	2.133	p = 0.987
EXPORTER	0.630	0.483	0.391	0.488	p < 0.0001	0.752	0.432	0.579	0.495	p < 0.0001
CAPINT*	0.065	0.111	0.128	1.258	p = 0.397	0.237	1.630	0.064	0.103	p = 0.111
PCM*	-0.604	13.608	-0.285	9.215	p = 0.689	-0.124	2.057	-0.082	2.728	p = 0.856
EAST	0.679	0.467	0.427	0.495	p < 0.0001	0.654	0.476	0.293	0.456	p < 0.0001
PS/EMP	0.041	0.079	0.014	0.047	p < 0.0001	0.040	0.070	0.019	0.052	p < 0.0001
Credit rating*	251.580	55.227	243.757	49.778	p = 0.012	237.835	38.596	236.203	37.346	p = 0.620
$\hat{P}$(X)	0.637	0.207	0.412	0.203	p < 0.0001	0.632	0.221	0.382	0.211	p < 0.0001
R&Dint	20.263	30.352	3.581	11.387	p < 0.0001	17.511	29.956	4.770	16.169	p < 0.0001
R&DEint	34.907	34.168	10.373	20.127	p < 0.0001	28.203	30.799	9.545	20.052	p < 0.0001
R&D	1.037	4.905	0.148	0.578	p < 0.0001	1.841	4.752	0.866	2.511	p = 0.001
R&D emp	9.760	16.745	2.056	4.922	p < 0.0001	17.162	27.517	6.333	17.416	p < 0.0001

	Low-Tech NTBFs					**Low-Tech Group NTBFs**				
	subsidized firms N_1=328		potential control group N_1=640		p-value of two-sided t-test on mean equality	subsidized firms N_1=121		potential control group N_1=350		p-value of two-sided t-test on mean equality
	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
EMP	57.845	55.165	43.659	46.869	p < 0.0001	86.901	62.376	78.14	68.088	p = 0.195
AGE	6.290	2.133	6.047	2.117	p = 0.093	6.413	2.052	6.04	2.162	p = 0.090
EXPORTER	0.506	0.501	0.272	0.445	p < 0.0001	0.570	0.497	0.423	0.495	p = 0.005
CAPINT*	0.104	0.165	0.108	0.180	p = 0.811	0.144	0.420	0.299	0.926	p = 0.061
PCM*	0.138	0.696	-0.861	19.937	p = 0.353	0.145	0.673	0.207	0.858	p = 0.501
EAST	0.872	0.335	0.639	0.481	p < 0.0001	0.744	0.438	0.414	0.493	p < 0.0001
PS/EMP	0.015	0.054	0.004	0.025	p = 0.0002	0.016	0.051	0.003	0.017	p = 0.008
Credit Rating*	244.379	38.679	246.089	53.959	p = 0.523	232.120	29.433	236.263	55.912	p = 0.338
$\hat{P}$(X)	0.506	0.224	0.255	0.188	p < 0.0001	0.427	0.224	0.201	0.162	p < 0.0001
R&Dint	4.620	11.313	0.696	1.687	p < 0.0001	3.492	6.874	1.178	5.226	p = 0.001
R&DEint	11.232	17.374	4.704	19.201	p < 0.0001	8.489	21.262	3.439	9.309	p = 0.013
R&D	0.195	0.348	0.074	0.633	p = 0.0001	0.480	1.028	0.224	1.144	p = 0.023
R&D emp	3.768	5.796	1.023	2.538	p < 0.0001	4.087	6.053	1.797	6.135	p = 0.0004

[a]: Industry dummies and time dummies not reported
*: For the variables Capint, PCM and Credit rating, the descriptive statistics are based on the actual observed observations. The observations for which the dummy was set to 1 and the missings to zero are thus not included.

Next to the summary statistics of the control variables, table 4 reports the summary statistics and t-tests on mean differences between the outcome variables. In general, these variables have the highest values for both NTBFs and Group NTBFs. In addition, all outcome variables differ significantly between subsidized firms and the control group. In all cases, the subsidized firms have higher intensities and more R&D expenditures and employees. From the descriptive statistics, it is unclear whether these differences can be attributed to the receipt of subsidies. We will apply a matching estimator, as outlined in the previous section, in order to unravel this question.

4 Estimation and results

4.1 Subsidy effect on NTBFs

When applying a matching estimator, we estimate in first intance a probit model on the receipt of subsidies. This probit model is estimated in order to obtain the propensity score. Table 5 presents the results of this estimation. In line with the results from the descriptive statistics, we find that companies located in East-Germany have a higher probability to receive subsidies. In addition, the results also confirm the higher probability of receiving subsidies if the patent stock is larger. Except for Group LTBFs, being an exporter has a positive effect on subsidy receipt. Other average significant differences in the descriptive statistics however are not apparent anymore in the probit estimation.

Having obtained a propensity score based on the estimation results of the probit estimation on subsidy receipt, we still have to restrict the sample to common support. In the previous section, we already stated that the matching estimator is non applicable if the overlap between the different subsamples is too small in terms of the characteristics controlled for. Table 6 shows how many observations have to be dropped for each firm class in order to assure a sufficient overlap between the treated and untreated firms under consideration. Next to the restriction of common support, we also impose a caliper threshold as we apply caliper matching. This caliper threshold serves as a maximum distance between treated and untreated firms. We chose a threshold of 0.05 in order to assure a precise and well-balanced matching. The third column of table 6 presents the number of observations that are lost after setting this threshold. The last column of table 6 shows how many treated observations can be successfully matched.

After setting the different thresholds, we pick the nearest neighbor out of the control group to find the best match for the treated firms. After matching, there are no statistically significant differences in the exogenous variables anymore. In line with this, the propensity score is also not significantly different between the two groups (results not shown here). Table 7 shows the outcome of the tests on overall model significance of the probit models on subsidy receipt after matching. As can be seen in the table, the null hypothesis that all coefficients in the regressions are jointly zero cannot be rejected for each type of firm, as expected in case of successful matching.

Table 8 presents the treatment effects on the outcome variables after matching by propensity score. As can be seen, almost all treatment effects are positive and significant. After matching, these

Table 5: Probit estimation on subsidy (SUB)

	(1) NTBF	(2) Group NTBF	(3) LTBF	(4) Group LTBF
ln(AGE)	-0.134	-0.252*	-0.133	0.220
	(0.101)	(0.135)	(0.118)	(0.184)
EXPORTER	0.562***	0.419***	0.395***	-0.000
	(0.089)	(0.138)	(0.107)	(0.167)
ln(EMP)	0.003	-0.010	0.047	0.313
	(0.160)	(0.260)	(0.230)	(0.360)
$\ln(EMP)^2$	0.007	-0.008	0.013	-0.035
	(0.025)	(0.036)	(0.034)	(0.050)
CAPINT	-0.109	0.863	0.388	-0.149
	(0.252)	(0.740)	(0.351)	(0.160)
D(CAPINT)	-0.209	-0.199	-0.307*	-0.424
	(0.137)	(0.217)	(0.181)	(0.285)
PCM	0.000	-0.008	0.009	-0.077
	(0.005)	(0.028)	(0.033)	(0.107)
D(PCM)	-0.163	-0.174	-0.371*	0.113
	(0.138)	(0.208)	(0.189)	(0.280)
EAST	1.008***	1.074***	1.054***	0.973***
	(0.090)	(0.120)	(0.127)	(0.164)
PS/EMP	3.279***	3.677***	5.404***	8.977***
	(0.665)	(0.992)	(1.348)	(2.732)
RATING	0.000	-0.001	-0.002*	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)
D(RATING)	0.209	-0.698	-0.441	-0.588
	(0.243)	(0.446)	(0.316)	(0.538)
Constant	-0.066	-0.170	-0.560	-3.019**
	(0.396)	(0.719)	(0.676)	(1.197)
Test on joint significance of industry dummies	$\chi^2(4) = 4.91$	$\chi^2(4) = 6.29$	$\chi^2(8)= 25.54$***	$\chi^2(8)= 11.13$
Test on joint significance of time dummies	$\chi^2(7) = 51.44$***	$\chi^2(7) = 4.61$	$\chi^2(7) = 23.31$***	$\chi^2(7) = 8.75$
Test on joint significance of ln(EMP) and $\ln(EMP)^2$	$\chi^2(2) = 1.49$	$\chi^2(2) = 1.49$	$\chi^2(2) = 7.95$**	$\chi^2(2) = 1.27$
Log-Likelihood	-708.289	-344.272	-490.596	-213.663
N	1247	619	968	471

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 6: Loss of subsidized observations due to a lack of common support and being out of the distance specified by the caliper threshold

sample	Initial sample size of subsidized firms	lack of common support	out of caliper threshold	final sample size of subsidized firms
NTBF	664	-4	-44	616
Group NTBF	315	-14	-44	257
LTBF	328	-7	-38	283
Group LTBF	121	-8	-16	97

Table 7: Significance of probit regressions after matching

sample	# obs	Wald$\chi^{2(23)}$	p-value[a]
NTBFs (strict definition)	1232	6.46	0.9997
Group NTBFs	514	5.83	0.9999
Low-tech NTBFs	566	15.28[b]	0.9653
Group low-tech NTBFs	194	21.29[b]	0.7723

[a]: t-statistics based on a ttest on the coefficients of the α on the different outcome variables
[b]: Due to different industry classification of low-tech NTBFs: Wald$\chi^{2(27)}$

significant results can be fully assigned to the receipt of subsidies. As a consequence, full crowding-out with regard to public funding can be, in general, rejected for all firm types studied. Nevertheless, the treatment effects differ between the different groups of firms. While crowding-out can be convincingly rejected for NTBFs, the effect of subsidies on R&D expenditures is insignificant for Group NTBFs. In addition, while for LTBFs, the treatment effects are at least significant at the 5% level, the treatment effect on R&D intensity for Group LTBFs is only significant at the 10% level and only the treatment effect on R&D employment is highly significant for these firms.

The table suggests that high-tech small young firms make, in general, more efficient use of subsidies than low-tech small young firms, whether they are independent or part of a group. This suggests that the fact of being part of a high-tech sector is an important determinant of efficient use of R&D subsidies. Within the group of high-tech firms, the independent ones, NTBFs, have higher treatment effects, except for R&D employment, which increases slightly more for Group NTBFs after subsidy receipt. The difference between independent and group firms in high-tech sectors cannot be found within the group of low-tech firms. While R&D intensity seems to be slightly higher after receiving subsidies for LTBFs, the other treatment effects are higher for Group LTBFs. This suggests that the factor being independent or being part of a group has different effects for high-tech and low-tech

Table 8: Treatment effects after matching

NTBF		**Group NTBF**		**Small Old firms**
Matched subsidized firms: 616		Matched subsidized firms: 257		
R&Dint	15.519***	R&Dint	9.543***	
R&DEint	23.204***	R&DEint	13.818***	
R&D	0.745***	R&D	0.580	
R&D emp	6.467***	R&D emp	9.311***	
LTBF		**Group LTBF**		
Matched subsidized firms: 283		Matched subsidized firms: 97		
R&Dint	3.167***	R&Dint	1.614*	
R&DEint	4.138**	R&DEint	5.745**	
R&D	0.091***	R&D	0.226**	
R&D emp	1.682***	R&D emp	2.054***	
Large young firms				**Large old firms**

firms. However, especially for the latter firms, these differences are only small and it is questionable whether they are also significant.

The next section evaluates whether the differences in treatment effects visible in table 8 are significant and especially whether it is correct to pose that NTBFs do make more efficient use of subsidies than all other small young firms.

4.2 Evaluation of the treatment effects

The results shown above give an overview of the treatment effects for the different firm classes. However, it remains unclear whether the visible differences are also significant. The significance of these differences can be assessed by regressing the individual treatment effects on dummies referring to the different firm types, with NTBF as the reference group for all firms that received subsidies. The constant term then reflects the treatment effect for NTBFs and the dummy coefficients present the difference in treatment effects with respect to NTBFs. In order to evaluate the differences of the treatment effects with respect to other firm types, we perform t-tests on the equality of the different coefficients of the firm types we want to compare.

While simply regressing the treatment effect on the different firm type dummies indicates to what extent the differences in treatment effects are significant, this does not account for other effects that may be influencing these differences. In order to control for other effects, we include extra control variables in the regressions on the treatment effects.

Czarnitzki and Licht (2006) found that input additionality has been more pronounced in Eastern Germany during the transition period than in Western Germany. It is thus possible that the differences in treatment effects between different firm types can be attributed to the fact that the firm type with higher treatment effects is mainly active in Eastern Germany. In order to control for potential different location effects, we include a dummy EAST in the regressions, taking the value 1 if the firm is located in Eastern Germany and 0 if it is located in Western Germany.

All firms included in the estimation of the treatment effect are subsidized firms, having received funding from at least one source. However, it is possible that some firms included in the sample received subsidies from both the European Union, the country and the different regions. Similarly, some firms might have been subsidized by two different funding sources. Czarnitzki and Lopes Bento (2011) differentiate between firms having received national funding, European funding and funding at both the national and the European level and find that, in terms of input, getting funding from both sources yields the highest impact. As a consequence, we should control for the number of subsidies received in order to capture potential effects of the number of subsidies received on the treatment effects. We do so by including two dummies 2SUB and 3SUB, referring to firms that received subsidies from 2 funding sources and all 3 funding sources respectively, with firms that received funding from only one source as the reference group.

While we already focus on small firms, it is still possible that amongst the different groups of firms the treated matched firms differ in terms of size. In order to control for potential differences in size, we introduce the number of employees in the regression (EMP). Next to controlling for size, we include seven time dummies in the estimation in order to control for business cycle effects. [1]

[1] Information on the different subsidy sources is not available for all years in the analysis. We have this information for the following waves of the survey: MIP1995 (1992-1994), MIP1999 (1996-1998), MIP2001 (1998-2000), MIP2003 (2000-2002), MIP2004 (2001-2003), MIP2005 (2002-2004) and MIP2007 (2004-2006). As a consequence, we had to drop one year when we control for subsidy sources in the regressions and as a consequence, only six time dummies could be included in these estimations.

Table 9: Comparison

	(1) RDint		(2) RDEint		(3) R&D		(4) R&D employment	
Group NTBF	-5.977**	-5.242*	-9.386***	-6.068**	-0.165	-0.848**	2.844	-0.576
	(2.643)	(2.890)	(2.797)	(2.758)	(0.352)	(0.404)	(2.409)	(2.232)
LTBF	-12.353***	-7.928***	-19.066***	-15.715***	-0.654***	-0.668***	-4.785***	-5.740***
	(1.525)	(1.607)	(2.188)	(2.458)	(0.195)	(0.222)	(0.859)	(1.063)
Group LTBF	-13.906***	-9.759***	-17.459***	-9.436***	-0.519**	-0.857**	-4.413***	-5.863***
	(1.515)	(1.837)	(2.954)	(3.638)	(0.215)	(0.339)	(1.005)	(1.568)
EAST		-1.036		-0.221		0.535		2.708
		(2.317)		(2.823)		(0.377)		(1.895)
2SUB		9.021***		6.284***		0.492**		2.698*
		(1.914)		(2.421)		(0.247)		(1.392)
3SUB		16.613***		21.821***		2.357**		15.578***
		(3.940)		(3.917)		(1.196)		(3.184)
EMP		-0.067***		-0.125***		0.014***		0.076***
		(0.016)		(0.017)		(0.005)		(0.022)
Constant	15.519***	15.089***	23.204***	22.608***	0.745***	-1.093	6.467***	-2.887
	(1.360)	(3.156)	(1.763)	(3.308)	(0.193)	(0.719)	(0.732)	(2.180)
F-test on joint significance of time dummies		1.87*		2.23**		0.62		1.21
N	1253	1047	1253	1047	1253	1047	1253	1047
r2	0.041	0.114	0.058	0.161	0.004	0.071	0.019	0.127
F	30.241	9.716	27.036	16.689	4.322	1.973	12.754	5.737
t-test on equality of Group NTBF and LTBF	7.03***	1.03	13.59***	11.48***	1.60	0.32	10.21***	5.28**
t-test on equality of Group NTBF and Group LTBF	10.93***	3.02*	6.14**	0.87	0.79	0.00	8.77***	4.42**
t-test on equality of LTBF and Group LTBF	2.62	1.38	0.35	2.87*	1.92	0.67	0.21	0.01
t-test on equality of 2sub and 3sub		3.30*		14.92***		2.20		14.99***

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 9 presents the results of the treatment effect regressions on R&D intensity, R&D employment intensity, R&D expenditures and R&D employment. For each treatment effect, both the basic regression without additional control variables and the extended regression are presented. The table reveals that the differences between high-tech and low-tech small young firms in table 8 are only convincingly prevalent for independent firms. NTBFs always have a higher input additionality than both LTBFs and Group LTBFs, even after including the control variables in the regressions. For Group NTBFs, we initially also find significant differences compared to LTBFs and Group LTBFs for all treatment effects. However, after including the additional control variables in the regression framework, these results change. First, the difference between the subsidy effect on R&D employment intensity of Group NTBFs and Group LTBFs becomes insignificant. In addition, the significant higher increase in R&D intensity that was found for Group NTBFs compared to LTBFs and Group LTBFs after receiving subsidies becomes at most weakly significant.

When focusing solely on low-tech firms, we never find a significant difference between effects of subsidies on independent and group firms. As a consequence, when solely focusing on these low-tech firms, a policy focus on independent small young firms does not seem to be efficient. For high-tech small young firms, on the other hand, the differentiation between independent firms and group firms seems to matter, although not for all treatment effects. In the basic regressions, the differences are only significant for the treatment effects on the intensity measures. In the extended regressions, the difference between the R&D expenditures treatment effect also become significant. On the other hand, the significance of the higher increase in R&D intensity for NTBFs as compared to Group NTBFs diminishes to the 10% level after the extra controls are included in the regression. Thus, in the extended regressions, only the subsidy effects on both R&D employment intensity and R&D expenditures are significantly higher for independent NTBFs. The results also reveal that the lower treatment effect that was found on R&D employment for NTBFs as compared to Group NTBFs is insignificant in the basic regression. In addition, as soon as the control variables are included in the regression, this coefficient, though still insignificant, becomes negative. This suggests that Group NTBFs do not make more efficient use of R&D subsidies in terms of R&D employment, as was initialy indicated by the treatment effects.

In general, the above findings suggest that, while policy mostly targets small young independent firms when deciding upon subsidy recipients, it is more important to base this decision in a first stage on sector of activity. Only when the target group is restricted to high-tech firms, it makes sense to distinguish between independent firms and group firms. Indeed, the only type of firm that convincingly makes more efficient use of subsidies, both in terms of R&D expenditures and in terms of R&D employment are NTBFs.

5 conclusion

Governments acknowledge the fact that small young firms are in need of R&D subsidies. However, in light of the 'Europe 2020' strategy, they increasingly focus on 'less and better' state aid, thereby trying to target small young firms that will most efficiently make use of their grants. While governments already actively target young, small independent firms and increasingly acknowledge the importance of sectoral differentiation, there is no decisive evaluation yet on the true importance of letting these factors have an influence on subsidy receipt of small young firms. As a consequence, in this study, we compare the effect of innovation subsidies on New Technology Based Firms (NTBF), Low Technology Based Firms (LTBFs) and their group counterparts, in Germany. NTBFs are small young independent high-tech firms, while LTBFs are small young independent firms active in low-tech sectors. We denote their group counterparts by Group NTBFs and Group LTBFs. We question and compare the input additionality effects on each of this firm types by estimating the effect of subsidies on R&D intensity, R&D expenditures, R&D employment intensity and R&D employment numbers.

In order to evaluate the impact of innovation subsidies on NTBFs, Group NTBFs, LTBFs and Group LTBFs, caliper matching is applied in order to correct for a potential selection bias. In general, our results reveal that full crowding-out with regard to public funding can be rejected for all firm types studied.

Nevertheless, not all treatment effects of the different firm types are equally high. In order to assess the differences in subsidy effects, we compare the treatment effects of the different firm types in a regression framework by regressing the treatment effect on the different firm types and additional control variables. Our results reveal that a pure differentiation based on being independent or not is not the most efficient way of distributing innovation subsidies to small young firms. Instead, in a first stage, the decision on how to distribute R&D subsidies should be based on sector of activity. Only when the target group is restricted to high-tech firms, it makes sense to distinguish between independent firms and group firms. Indeed, the only type of firm that convincingly makes more efficient use of subsidies, both in terms of R&D expenditures and in terms of R&D employment are NTBFs.

For future research, the availability of a balanced panel would be useful in order to introduce a time-series dimension into the econometric setup. In addition, we could only assess whether a firm has received a subsidy or not, without being able to assess what the different subsidies for different firms exactly entail. Indeed, although we already have valuable information on the different subsidy sources, we do not know how much aid is actually given to a firm. Introducing this latter aspect in the estimations would be very interesting for further research.

References

Aerts, K. and Czarnitzki, D. (2004), 'Using innovation survey data to evaluate R&D policy: the case of Belgium', *ZEW working paper* **04-55**.

Aghion, P. and Howitt, P. (1998), 'Capital accumulation and innovation as complementary factors in long-run growth', *Journal of Economic Growth* **3**, 111–130.

Almus, M. and Czarnitzki, D. (2003), 'The effects of public r&d subsidies on firms' innovation activities: the case of Eastern Germany', *Journal of Business and Economics Statistics* **21**, 226–236.

Almus, M. and Nerlinger, E. (1999), 'Growth of New Technology Based Firms: which factors matter?', *Small Business Economics* **13**, 141–154.

Angrist, J. (1998), 'Estimating the labor market impact of voluntary military service using social security data', *Econometrica* **66**, 249–288.

Arrow, K. (1962), Economic welfare and the allocation of resources for invention, *in* R. Nelson, ed., 'The rate and direction of inventive activity: economic and social factors', Princeton University Press, pp. 609–625.

Busom, I. (2000), 'An empirical evaluation of the effects of R&D subsidies', *Economics of Innovation and New Technology* **9**, 111–148.

Cerulli, G. (2010), 'Modelling and measuring the effect of public subsidies on business r&d: A critical review of the econometric literature', *The economic record* .

Cochran, W. and Rubin, D. (1973), 'Controlling bias in oberservational studies: a review', *Sankhya* **Ser. A 35**, 417–446.

Colombo, M. G., Giannangeli, S. and Grilli, L. (2008), 'A longitudinal analysis of public financing and the growth of New Technology-based Firms: do firms' age and applicants' evaluation methods matter?', *Unpublished Manuscript* .

Colombo, M. G. and Grilli, L. (2006), 'Supporting high-tech start-ups: lessons from Italian technology policy', *International Entrepreneurship and Management Journal* **2**, 189–209.

Colombo, M. G. and Grilli, L. (2010), 'On growth drivers of high-tech start-ups: Exploring the role of founders' human capital and venute capital', *Journal of Business Venturing* **25**(6), 610–626.

Colombo, M. G., Grilli, L. and Murtinu, S. (2011), 'R&D subsidies and the performance of high-tech start-ups', *Economics Letters* **112**, 97–99.

Czarnitzki, D. and Hottenrott, H. (2011), 'R&d investment and financing constraints of small and medium-sized firms', *Small Business Economics* **36**, 65–83.

Czarnitzki, D. and Hussinger, K. (2004), 'The link between R&D subsidies, R&D spending and technological performance', *ZEW working paper* **4-56**.

Czarnitzki, D. and Licht (2006), 'Additionality of Public R&D Grants in a Transition Economy: the Case of Eastern Germany', *The Economics of Transition* **14**, 101–131.

Czarnitzki, D. and Lopes Bento, C. (2010), 'Evaluation of public R&D policies: A cross-country comparison', *CEPS/INSTEAD discussion paper* .

Czarnitzki, D. and Lopes Bento, C. (2011), 'Innovation Subsidies: Does the Funding Source Matter for Innovation Intensity and Performance? Empirical Evidence from Germany', *ZEW discussion paper no 11-053* .

David, P., Hall, B. and Toole, 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. and Wahba, S. (1999), 'Causal effects in nonexperimental studies: reevaluating the evaluation of training programs', *Journal of the American Statistical Association* **94**, 1053–1062.

Dixit, A. K. and Pindyck, R. S. (1994), *Investment under Uncertainty*, Princeton University Press.

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**, 263–292.

EC-DG Research and Innovation (2011), 'State of the innovation union'.

Geroski, P. and Toker, S. (1996), 'The turnover of market leaders in UK manufacturing industry, 1979-86', *International journal of industrial organization* **14**, 141–158.

Gonzales, X., Jaumandreu, J. and Pazo (2005), 'Barriers to innovation and subsidy effectiveness', *RAND Journal of Economics* **36**, 930–949.

Gonzales, X. and Pazo, C. (2008), 'Do public subsidies stimulate private r&d spending?', *Research Policy* **37**, 371–389.

Goolsbee, A. (1998), 'Does R&D Policy primarily benefit scientists and engineers?', *American Economic Review* **88**, 298–302.

Griliches, Z. and Mairesse, J. (1984), Productivity and R&D at the firm level, *in* Z. Griliches, ed., 'R&D, Patents and Productivity', University of Chicago Press: Chicago, IL.

Grilli, L. and Murtinu, S. (2012), 'Do public subsidies affect the performance of new technology-based firms? the importance of evaluation schemes and agency goals', *Prometheus: Critical Studies in Innovation* **30**, 97–111.

Hall, B. (1990), 'The impact of corporate restructuring on industrial research and development', *Brooking Papers on Economic Activity* **1**, 85–136.

Hall, B. and Lerner, J. (2010), The financing of r&d and innovation, *in* B. Hall and N. Rosenberg, eds, 'Economics of innovation', Elsevier.

Heckman, J., Ichimura, H., Smith, J. and Todd, P. (1998), 'Characterizing selection bias using experimental data', *Econometrics* **66**, 1017–1098.

Heckman, J., Ichimura, H. and Todd, P. (1998), 'Matching as an econometric evaluation estimator', *Review of Economic Studies* **65**, 261–294.

Heckman, J., Lalonde, R. and Smith, J. (1999), The economics and econometrics of active labour market programs, *in* A. Ashenfelter and D. Card, eds, 'Handbook of Labour Economics', Amsterdam.

Heckman, J., Smith, J. and Clements, N. (1997), 'Making the most out of program evaluations and social experiments: accounting for heterogeneity in program impacts', *Review of Economic Studies* **64**, 487–536.

Himmelberg, C. and Petersen, B. (1994), 'R&d and internal finance: a panel study of small firms in high-tech sectors', *Review of Economics and Statistics* **76**, 38–51.

Imbens, G. and Wooldridge, J. (2009), 'Recent developments in the econometrics of program evaluation', *Journal of Economic Literature* **47**, 5–86.

Jaffe, A. (1986), 'Technological opportunity and spillovers of R&D: evidence from firm's patent, profits, and market value', *American Economic Review* **76**, 984–1001.

Lach, S. (2002), 'Do r&d subsidies stimulate or displace private r&d? evidence from israel', *Jounal of Industrial Economics* **50**, 369–390.

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 Evaluatoin of Labour Market Policies', Physica, pp. 43–58.

Licht, G. and Nerlinger, E. (1998), 'New technology-based firms in Germany: a survey of the recent evidence', *Research Policy* **26**, 1005–1022.

Little, A. D. (1977), 'new technology-based firms in the United Kingdom and the Federal Republic of Germany', *A report prepared for the Anglo-German foundation for the study of industrial society, London* .

Mansfield, E. (1962), 'Entry, gibrat's law, innovation and the growth of firms', *American Economic Review* **52**(5), 1023 – 1051.

Mansfield, E. (1988), 'Industrial R&D in Japan and the United States: a comparative study', *American Economic Review* **78**, 223–228.

Moncada, P., Ciupagea, C., Smith, K., Tï¿½bke, A. and Tubbs, M. (2010), 'Does Europe perform too little corporate R&D? a comparison of EU and non-EU corporate R&D performance', *Research Policy* **39**, 523–536.

Nelson, R. (1959), 'The simple economics of basic scientific research', *Journal of political economy* **49**, 297–306.

Pindyck, R. (1991), 'Irreversibility, uncertainty, and investment', *journal of economic literature* **29**, 1110–1148.

Reinkowski, J., Alecke, B., Mitze, T. and Untiedt, G. (2010), 'Effectiveness of pulic R&D subsidies in East Germany: is it a matter of firm size?', *Ruhr economic papers* **204**.

Romer, P. (1990), 'endogenous technical change', *Journal of political economy* pp. 71–102.

Rosenbaum, P. and Rubin, D. (1983), 'The central role of the propensity score in observational studies for causal effects', *Biometrika* **70**, 41–55.

Rubin, D. (1977), 'Assignment to treatment group on the basis of covariate', *Journal of Educational Statistics* **2**, 1–26.

Scherer, F. (1965), 'Corporate inventive ouput, profits, and growth', *journal of political economy* **73**(3), 290–297.

Schneider, C. and Veugelers, R. (2010), 'On young highly innovative companies: why they matter and how (not) to policy support them', *industrial and corporate change* **19**(4), 1–39.

Schumpeter, J. (1942), *Capitalism, Socialism and Democracy*, New York, Harper and Row.

Stiglitz, J. and Weiss, A. (1981), 'Credit Rationing in Markets with Imperfect Information', *American Economic Review* **71**, 393–410.

Storey, D. and Tether, B. (1998), 'New technology-based firms in the european union: an introduction', *Research Policy* **26**(9), 933 – 946.

Veugelers, R. (2008), 'The role of SMEs in innovation in the EU: a case for policy intervention?', *Review of business and economics* **53**(3), 239–262.

Wallsten, S. (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**, 82–100.

Appendix

Table A1: Industry structure

Industry	Description	NTBF	group NTBF
1	Manufacture of chemicals and chemical products ;Manufacture of pharmaceuticals, medicinal chemicals and botanical products	89	64
2	Manufacture of machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment; Building and repairing of ships and boats ; Manufacture of aircraft and spacecraft;	235	132
3	Manufacture of office machinery and computers; Manufacture of electrical machinery and apparatus n.e.c.; Manufacture of radio, television and communication equipment and apparatus; Manufacture of medical, precision and optical instruments, watches and clocks;	276	142
4	Research and development; Other Business activities	476	185
5	Computer and related activities	171	96
	Total number of Observations:	1247	619
		LTBF	Group LTBF
6	Manufacture of food products, beverages and tobacco	42	23
7	Manufacture of textiles	61	21
8	Manufacture of wood and wood products; manufacture of pulp, paper and paper products; publishing and printing;	66	35
9	Manufacture of coke, refined petroleum products and nuclear fuel; Manufacture of rubber and plastic products	89	48
10	Manufacture of basic metals and fabricated metal products	179	59
11	Fishing; mining and quarrying; Mineral products; Furniture; other industries; Waste collection, treatment and disposal activities; materials recovery; Other services	245	133
12	Wholesale and retail trade and repair of motor vehicles and motorcycles	133	50
13	Transportation, storage ; Financial and insurance activities	137	89
14	Communication services	16	13
	Total number of Observations:	968	471