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by

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R&D SUBSIDIES TO START-UPS – EFFECTIVE DRIVERS OF PATENT ACTIVITY AND EMPLOYMENT GROWTH?

Uwe Cantner^a and Sarah Kösters^b

April 2009

Abstract

The present paper investigates the effectiveness of R&D subsidies given to start-ups. Taking an aggregate view rather than evaluating a single program, we estimate the impact of R&D subsidies on start-ups' employment growth and their patent output. A unique data set on start-ups in the East German county of Thuringia allows us to focus on those start-ups that conduct R&D within the first three business years. We conduct propensity score matching to address the selection bias between subsidized and non-subsidized start-ups. We find that R&D subsidies lead to an increase in employment growth of about 66%. Furthermore, subsidized start-ups show a 2.8 times higher patent output. These estimates provide evidence for the additionality of R&D subsidies within the first three business years. Moreover, our analysis points to the special group of academic spin-offs which excels in the novelty of business ideas and patent activity. For some of these high-tech start-ups, no non-subsidized counterparts can be found. This might be attributed to the policy focus on academic spin-offs, which has led to a successful targeting of R&D support schemes.

Key words: R&D subsidies; start-ups; policy evaluation

JEL classification: O38, L26, H50, C14

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1. INTRODUCTION

Newborn firms as well as small and medium sized companies contribute crucially to technological change through research and development (R&D) and innovation (Acs and Audretsch, 1990; Audretsch, 2006). This has led to a rise in policy programs targeted at the R&D of (nascent) entrepreneurs and their newborn firms all over the world (Lerner, 1999). Fostering R&D and technology-oriented start-ups is a stated aim of promotional initiatives such as the “High-Tech Strategy for Germany”, which announced additional R&D funds of 6bn Euro between 2006 and 2009 (BMBF, 2006). Especially in East Germany, R&D support schemes focus on small and medium enterprises as well as start-ups (Deutscher Bundestag, 2005).

Rather traditionally, the presumed existence of market failure provides a rationale for public R&D subsidies. The presence of R&D spillovers – which have been studied, for example, by Griliches (1992) and Jaffe (1996) – is one argument in favor of public intervention, since the limited appropriability of returns from R&D induces firms to invest below the social optimum in R&D. A second argument in favor of subsidizing R&D is based on information imperfections on the part of financial institutions. Sunk and firm-specific investment, low collateral value, and the high uncertainty of returns impact the financing conditions for R&D projects. This holds especially true for newborn firms which lack the necessary size to cross-subsidize R&D projects and to diversify the risks from innovative activity. In addition, they lack a track record to signal their creditworthiness to private investors. However, their R&D activity might still be socially beneficial by inducing knowledge spillovers as well as by challenging incumbents and thus ensuring competitive markets. Based on these three failures, public intervention could be justified and public expenditures may help overcome a lack of private investment in uncertain R&D projects and at the same time may certify the high quality of the R&D projects for other potential investors (Lerner, 1999).

However, the underlying reasons for policy intervention are not beyond dispute. The arguments opposing R&D subsidies and entrepreneurship policies are traditionally based on windfall gains and market distortions. First, windfall gains arise when companies would have performed the R&D project irrespective of public subsidies. Wallsten (2000) points out that efficient R&D subsidy should only be given to R&D projects that have positive net social benefits but negative net profits for the innovating firm. Hence, R&D subsidies should complement rather than crowd out private R&D investments. Second, market distortions occur because public support schemes equalize ex-ante less efficient and more efficient firms and in this way distort market selection as well as the learning processes of founders. This means that subsidization is an ‘artificial seedbed’ for less efficient firms, which would have been induced to leave the market if they had not received assistance (Santarelli and Vivarelli, 2006; Stam et al., 2007). This (potential)

crowding out of non-subsidized firms makes some authors oppose entrepreneurship policy schemes altogether (Parker, 2007).

Notwithstanding the theoretical arguments against public intervention, there is public money invested in R&D schemes. To ensure that taxpayer's money is spent effectively and efficiently, as well as to guide further policy-making, they have to be evaluated. Although policy evaluation is commonplace and part of most policy initiatives, Lerner (1999) notes that "public subsidisation of small firms has attracted virtually no scrutiny". Most evaluations only monitor the take-up of schemes and recipients' opinions, especially their views of the differences made by the assistance, and not the effectiveness and efficiency of the intervention. In fact, this mere monitoring of R&D schemes is not able to reveal any causal effects.

The present study attempts to overcome this gap and examines the effectiveness of R&D support schemes available to start-ups in innovative industries in the East German county of Thuringia. Doing so, we take an aggregate view and analyze the effectiveness of the subsidy environment – instead of a specific subsidy program – which young technology-oriented firms face. This perspective is especially promising when considering the great variety of different and often overlapping policy programs targeted at R&D¹. We thus evaluate a mixture of different but similar programs all available to Thuringian start-ups engaged in R&D within the first three business years. Our analysis is based on a random sample of innovative start-ups in innovative industries and focuses on those conducting R&D.

Since the objectives of single policy programs are often vague or non-existent (Storey, 2000), we examine two different performance measures, each capturing private returns of (subsidized) R&D activities: employment growth and innovation output (i.e. patent applications). We first argue that effective subsidies must lead to increasing R&D activity, which manifests in employment growth. Second, subsidies that foster the R&D activity of start-ups should also lead to higher innovation output measured by patent applications.

Identifying the impact of R&D support schemes ideally would require a counterfactual analysis. As this is not possible, one compares assisted firms with an appropriate control group of other firms (Storey, 2000). The set-up of a control group must consider that the allocation of public R&D funds cannot be assumed to be arbitrary. On the one hand, a strategy of policymakers might be to grant public means to promising ventures ("picking the winners"). On the other hand, public R&D funds might back firms with less promising R&D projects. If those sources of potential selection are ignored, the evaluation of the effects of public assistance will be biased.

¹ Bundestag (2005) provides insights into the volatile subsidy environment that East German firms face with regard to public R&D funds.

In order to overcome that possible selection bias in our policy evaluation, we apply propensity score matching (Rosenbaum and Rubin, 1983). The idea of this methodology is to assign to each assisted start-up a “statistical twin”, i.e. a start-up that has not been subsidized but that nevertheless has a similar probability of receiving public R&D funds. In this way, we create an adequate control group to estimate the causal effects of public R&D programs on employment growth and patent applications of subsidized firms.

The remainder of the paper is structured as follows. Previous studies on the effectiveness of R&D support schemes are discussed in section 2. Section 3 presents the evaluation framework. The assumptions and the procedure of the potential outcome approach are then applied to our founder dataset in section 4. Section 5 presents the results and their robustness. Finally, section 6 concludes.

2. LITERATURE REVIEW

The rise of R&D support schemes is accompanied by a growing literature on the effectiveness of R&D-subsidies. These studies differ with regard to their data bases and the level of aggregation, ranging from country-, industry- and firm-level analyses to experimental studies.

The straightforward approach in the typical econometric literature is regressing some measure of private R&D on public R&D to determine complementarity or substitutability of public R&D subsidies². Here, the effectiveness of R&D subsidies is related to firm-internal decision processes: Public R&D-funds might be either directed to projects that would have been undertaken anyway, leading to full or partial crowding out (substitution) of private investment, or they might stimulate additional private R&D effort, implying additionality or complementarity of R&D subsidies. David et al. (2000) conclude that the evidence on the effectiveness of publicly funded R&D schemes is mixed. This can be attributed to methodological differences as well as to the fact that most studies concentrate on the evaluation of one specific program. As these schemes differ in, e.g., program design, extent of financial support and regional scope, different results from evaluations are to be expected.

Alternatively, an increasing number of studies suggest a more indirect approach to the evaluation of the effectiveness of R&D schemes (David et al., 2000). These studies estimate the impact of R&D schemes on particular outcome variables, such as employment, patent applications and sales. In the absence of indicators for the social returns of subsidized R&D projects, these outcome variables indicate private returns and tend to capture effects beyond that level. On this basis, if subsidized firms reallocate public R&D funds to other means than publicly intended

² David et al. (2000) and Klette et al. (2000) provide extensive surveys.

(namely additional R&D activities), subsidized firms and their non-subsidized counterparts should not differ with respect to both the inputs to the R&D activity (e.g., measured by (R&D) employment growth) and the output of the R&D process (e.g., measured by patent applications).

Analyzing the effectiveness of R&D subsidies with regard to employment is justified for primarily three reasons: First, most R&D support programs focus on supporting R&D labor cost and other running costs, accounting for the fact that most R&D expenditure in small firms are spent for the salaries of scientists and engineers (Himmelberg and Petersen, 1994). Hence, additional R&D activity should be best captured by R&D-related employment growth. Second, grants might not only impact employment directly related to the subsidized R&D project; if R&D subsidies increase commercial opportunities, firms might employ additional personnel to expand production (Wallsten, 2000). Third, employment effects are regarded as a proxy for the social returns of R&D support schemes. High employment growth characterizes innovative high tech start-ups, which spur structural change and account for overall positive employment effects (Fritsch, 2008).

The Small Business Innovation Research (SBIR) scheme, a US program targeted at R&D projects of small firms, has been evaluated with regard to its employment effects (Lerner (1999) and Wallsten (2000)). Lerner compares SBIR awardees with firms of similar size and industry as well as with firms of similar size from the same region that have not received SBIR funds. He finds that firms having obtained SBIR funds in the period 1983-1985 grew significantly faster with respect to employment and sales between 1985 and 1995 (however, only in regions with substantial venture capital). Wallsten (2000) adopts a somewhat stronger experimental design and explicitly addresses the problem of endogeneity — the receipt of subsidies might induce employment growth, but at the same time high-performance firms might be also more likely to receive funds. Wallsten pursues an instrumental variable approach to address this selection bias and comes to a less favorable conclusion regarding the program's effectiveness. He shows that firms with more employees and patents are more likely to receive SBIR funds. Wallsten points out that the average recipient exhibits annual sales of more than \$4 million and employs more than 40 people and is as a result far from being the stereotypical entrepreneur. Whereas firms with more employees are more likely to receive subsidies, these, in turn, do not affect employment. Moreover, Wallsten's results suggest that public R&D funds lead to a crowding out of private investments in R&D. Studies explicitly distinguishing between the effects of the subsidy on aggregate employment and on aggregate expenditure suggest that subsidies affect wages of R&D personnel, since labor supply in R&D is strongly inelastic (Goolsbee, 1998; Wolff and Reinthaler, 2008).

Other studies examine the effectiveness of R&D subsidies looking at patent applications of subsidized and non-subsidized firms. Patents are a widely used measure for innovation output due to their availability and standardization. Furthermore, they have been found to be in close temporal proximity to actual R&D activity (Hall et al. 1986). However, the shortcomings of patent statistics, namely their heterogeneous – and often inconsiderable – economic value and varying propensities to patent across industries, are well known (see Griliches (1990) for a survey). Czarnitzki and Licht (2006) analyze the additionality of R&D subsidies with respect to innovation input (measured as private R&D expenditure) and innovation output (proxied by patent applications) for German firms in the mid to late 1990s. In a first step, they find that R&D grants positively impact private R&D investment. In a second step, they investigate whether additional R&D investments induced by subsidies improve innovation results. Subsidized firms in East Germany turn out to have both a significantly higher likelihood of having applied for a patent and a higher number of patent applications. Hence, for East Germany, there is no evidence that government-induced R&D is less productive than purely privately financed R&D activity.

Czarnitzki et al. (2007) analyze the impact of R&D subsidies and collaboration on the patenting activity for a sample of Finnish and Western German firms in the mid to late 1990s. They interpret R&D collaboration and subsidies as heterogeneous and conduct econometric matching to account for selection bias. Looking at firms not engaged in R&D cooperation, subsidies stimulate only the patent output of Finnish firms. (Western) German firms receiving R&D subsidies for individual research do not show a higher patent output (measured by a dummy which indicates if a firm has filed at least one patent). However, collaborative R&D activity (both subsidized and non-subsidized) stimulates patent activity as well as R&D intensity (R&D expenditure / sales) in both countries.

The studies reviewed so far look at the effectiveness of R&D support schemes at the level of established firms. There are only a few studies assessing the effectiveness of R&D schemes at the level of newborn firms. Koga (2005) analyzes panel data of Japanese high-technology firms that were all founded after 1989. He finds that the receipt of public R&D funds impacts positively on the (natural logarithm of) company-funded R&D. This complementary relationship between public and private R&D investment holds with and without considering a time lag between the receipt of R&D subsidies and private R&D investment one year later. However, when the dataset is split and only start-ups younger than six years are considered, R&D subsidies no longer show positive effects on private R&D investment. Koga's results suggest that newborn firms do not have a strong incentive to conduct additional R&D, as they are confined by their initial funds. Instead, mature firms and growth-oriented young firms are more likely to allocate public R&D funds to additional R&D. Lerner (1999) offers a similar explanation when he asks for more studies to

analyze the long-run effects of R&D grants. He puts forward the proposition that small high-technology firms are often organized around one key researcher. For these small and/or young firms, it may not be possible to accelerate the project's progress by employing more researchers or technicians.

Based on the literature just reviewed, our analysis focuses on young, start-up firms and takes the indirect approach of evaluating the effectiveness of R&D support schemes. The outcome variables considered are employment growth and patent applications.

3. THE EVALUATION FRAMEWORK

Evaluating the effectiveness of R&D support schemes for start-up firms requires a methodological approach allowing us to compare the performance of a firm with and without having received the support. Since the latter, counterfactual outcome, is not available, a special method has been developed to tackle this issue, this being the application of so-called matching models.

The potential outcome approach

When estimating causal effects with observational data, the problem arises that individual treatment effects are impossible to determine since we cannot observe the subsidized firm's performance if it had not been subsidized, and vice versa. We follow Roy (1951) and Rubin (1974) in their formalization of the potential outcome approach. We are interested in the *average treatment effect for the treated* (ATT), i.e. the expected differential economic performance of subsidized firms which can be attributed to the receipt of public subsidies. The treatment indicator, D , equals 1 if the firm receives subsidies; the indicator is coded 0 otherwise. The outcome for each firm is then defined as Y^1 if a firm's R&D is subsidized; a firm's outcome is denoted Y^0 in the case of no subsidies. With E as the expectation operator, the ATT can thus be defined as

$$(ATT) \quad E(Y^1 - Y^0 | D = 1) = E(Y^1 | D = 1) - E(Y^0 | D = 1) \quad (1)$$

A firm can only be subsidized or non-subsidized, so only one of the outcomes is observed. The outcome that cannot be observed is termed the counterfactual outcome. With non-experimental data, this counterfactual outcome $E(Y^0 | D = 1)$ cannot be substituted with $E(Y^0 | D = 0)$, because subsidized firms are supposed to be a selective group that would show different performance even in the absence of any subsidization.

In order to approach the counterfactual outcome, the selection of firms into treatment is assumed to be based on observables. The *conditional independence assumption* (CIA) states that, given a set of observable exogenous (not affected by the treatment) characteristics, X , potential outcomes are independent of the treatment assignment:

$$(CIA) \quad D \perp (Y^1, Y^0) \mid X \quad \forall X \quad (2)$$

To put it another way, if one can fully control for observable differences in characteristics between the subsidized and non-subsidized firms, the outcome that would result in the absence of any subsidies is the same in both cases. Consequently, if the CIA holds, the matching process can be compared to creating an experimental dataset, in that, conditional on observed characteristics, the selection process is random. Obviously, the CIA is a strong assumption. Since we employ a rich dataset which should contain comprehensive information on the determinants of both subsidization and outcome, we are confident in maintaining such a strong assumption.

Implicit in this notation is the *stable unit treatment value assumption* (SUTVA) which states that the subsidization does not impact on any firms other than those that are explicitly treated and whose outcome is denoted Y^1 (Rubin, 1991). In our context, this implies that R&D subsidies do not impact on non-subsidized firms by market effects or knowledge spillovers. Thus, SUTVA rules out general equilibrium effects of R&D subsidies. However, interaction effects can both over- and underestimate the ATT. On the one hand, the ATT is overestimated when the employment growth of subsidized firms is realized at the expense of non-subsidized firms. On the other hand, non-subsidized firms might profit from knowledge spillovers generated in subsidized firms, which leads to an underestimation of the subsidy's impact. Since these mechanisms of action are difficult to identify empirically, we follow the SUTVA and ignore general equilibrium effects. However, we indirectly account for different interaction effects by examining employment growth and patent output as outcome variables.

Propensity Score Matching

Subsidized and non-subsidized firms are matched on the basis of important, exogenous characteristics, X . Increasing the number of observable covariates constitutes a practical constraint, because the chances of finding a control unit decrease the greater the number of characteristics used in the match. Rosenbaum and Rubin (1983) propose the use of propensity score matching to solve this problem of dimensionality. The basic idea is not to match on covariates directly, but to match on a function of the covariates X which describes the propensity to receive treatment, i.e. $P(D=1 \mid X) = P(X)$. This predicted probability of group membership $P(X)$ – i.e., subsidization vs. non-subsidization – is usually obtained from logistic regression. Rosenbaum and Rubin (1983) show that matching on a single index, which reflects the probability of participation, could result in consistent estimates of the treatment effect in the same way as matching on all covariates. The CIA based on the propensity score is then given by

$$(CIA \text{ based on propensity score}) \quad D \perp (Y^1, Y^0) \mid P(X) \quad \forall X \quad (3)$$

Propensity score matching, however, cannot entirely solve the problem of having no appropriate matches, because propensity scores might strongly differ between subsidized and non-subsidized firms. The additional assumption of common support ensures that the propensity scores of subsidized and non-subsidized firms overlap, i.e. persons with the same X values have a positive probability of being either subsidized or non-subsidized. More technically, observations are only regarded if their propensity score values show a positive density within the group of subsidized as well as non-subsidized firms. The region of common support should be substantial. Failing this, a considerable error may be introduced. This might happen, if only the worst cases from the non-subsidized “comparison” group are compared with only the best cases of all subsidized firms.

Matching algorithms

There are various matching algorithms which all contrast the outcome of a treated firm $i \in I_1$ with a weighted average of the outcome of (some) control group observations, $j \in I_0$. Following the notation of Caliendo (2006), the average treatment effect for the treated (ATT) can be stated as

$$ATT = \frac{1}{N_1} \sum_{i \in I_1} [Y_i^1 - \sum_{j \in I_0} W_{N_0}(i, j) Y_j^0] \quad (4)$$

with Y_i^1 denoting the outcome of the treated firm i and Y_j^0 the outcome of untreated firms j . N_1 (N_0) is the number of observations in the treatment group I_1 (control group I_0). The outcome of i is contrasted with the average weighted outcome of the control group, where the weights are given by $W_{N_0}(i, j)$. Usually, the weights the weighting function assigns to the untreated firms are higher the closer the untreated firms and the treated firm are with respect to the observed characteristics. The total weight of all controls adds up to one for each treated firm, i.e.

$$\sum_{j \in I_0} W_{N_0}(i, j) = 1 \quad \forall i.$$

The matching algorithms differ in terms of the construction of the weighting functions and the definition of potential “neighborhoods” which restrict the number of observations that serve as a comparison unit. An overview of different matching algorithms can be found in Heckman et al. (1998) as well as in Smith and Todd (2005). Smith (2000) points out that all matching estimators asymptotically yield the same results, since they all approach only exact matches as the sample size grows. However, the results from different matching algorithms can differ in small samples, pointing to a trade-off between quality and quantity of the matches. A matching algorithm yielding few but good matches will lead to biased estimates, whereas a matching procedure with many but

poor matches yields higher variance. Thus, the choice of the matching algorithm depends on the available data structure.

In our evaluation, we apply kernel matching. This matching estimator uses all units in the control group to construct a match for each treated firm. Therefore, it promises to exploit our data best, since the sample is relatively small and there are almost as many subsidized firms as non-subsidized control firms (see section 4.1). The major advantage of kernel matching is the lower variance, since more information for the construction of the counterfactual is used. However, the use of more information is at risk to include bad matches. Kernel matching employs the following weights,

$$W_{N_0}(i, j) = \frac{G_{ij}}{\sum_{k \in I_0} G_{ik}} \quad (5)$$

with G_{ik} denoting a kernel function $G[(P_i - P_k)/h]$. The implementation of kernel matching involves two choices: the choice of the kernel function G_{ik} as well as the choice of the bandwidth parameter h . If a symmetric, nonnegative, unimodal kernel is employed, higher weights are attached to observations close in terms of the propensity score P . DiNardo and Tobias (2001) note that the kernel employed is relatively unimportant in practice, but the choice of the bandwidth parameter matters. The bandwidth parameter h determines a trade-off between a small variance and an unbiased estimate of the true underlying density function (DiNardo and Tobias, 2001). On the one hand, the higher the bandwidth parameter, the smoother is the estimated density function, which leads to a better fit and a decreasing variance between the estimated and the true underlying density function. On the other hand, a high bandwidth parameter risks biased estimates, because underlying features of the true density function might be smoothed away. There are two methods of bandwidth selection: the method of cross-validation and the plug-in-method (Galdo, Smith and Black, 2007). We employ the latter and follow Silverman's (1986) frequently used rule-of-thumb to determine the bandwidth h and thus balance bias and variance. $h = 0.9 \cdot A \cdot n^{-1/5}$ is the optimal bandwidth for a Gaussian (normal) kernel. Herein n denotes the number of observations and the term $A = \min(\text{standard deviation}, \frac{\text{interquartile range}}{1.34})$ accounts for the distribution of the propensity score.

4. EMPIRICAL ANALYSIS

After introducing our database and the employed variables (section 4.1), we estimate the propensity score and look for the region of common support (section 4.2). In section 4.3, Kernel matching is performed and the matching quality is assessed.

4.1 THE DATA

Data for this study were collected within the Thuringian Founder Survey (Thüringer Gründer Studie), which is an interdisciplinary project on the success and failure of innovative start-ups in the eastern German state of Thuringia. The database draws from the commercial register for commercial and private companies (Handelsregister, Abteilung A/B) in Thuringia and includes 2,971 start-ups in innovative industries registered between 1994 and 2006. Innovative industries, according to ZEW classification (Grupp and Legler, 2000), comprise ‘advanced technology’ and ‘technology-oriented services’.

The survey population consists of 4,215 founders (first registered owner-managers) who registered a new entry in the Handelsregister between 1994 and 2006. This design made it possible to interview not only founders of active companies but also founders of ventures that had failed. From the survey population, we selected a random sample so that 3,671 founders of start-ups were contacted. Due to team ventures, this corresponds to 2,604 start-ups in innovative industries. Between January and August 2008, we conducted 633 face-to-face interviews with solo entrepreneurs or with one member of a start-up team (a response rate of about 21%). The 71 start-ups that turned out not to be genuinely new (e.g. they were a new branch or new business area of an existing company) were removed. A further 17 interviews had to be deleted due to concerns over interview quality. In order to exclude any effects of the German reunification, only start-ups with a first business year later than 1993 were considered³. This reduced the number of valid interviews to 450.

The structured interviews were conducted by the members of the research project. We were supported by student research assistants who were trained in various sessions in December 2007. On average, an interview took one and a half hours. The interviews covered a broad set of questions regarding socio-demographic and psychological data of the founder. Moreover, we asked for founder’s activities along the founding process. Economic data focused on the time before the first business year and the first three business years. Retrospective data relating to events in the

³ We defined the first business year as the time when accounting started either because of obligations from the commercial register or because of first revenues. This does not necessarily correspond to the date of registration in the Handelsregister.

founder's life and to the business history were collected using a modified version of the Life-History-Calendar (Belli et al., 2004), which increases the validity of retrospective data.⁴

The majority of venture set ups in the sample, i.e. 273 start-ups (61.2%), reported having conducted R&D within the first three business years. These R&D performing start-ups constitute the unit of investigation in this article. Public funds in support of R&D were given to 116 firms (42.5% of all R&D performing start-ups)⁵. Figure 1 shows the first business year of all interviewed start-ups and pictures the shares of those start-ups that performed R&D as well as received R&D subsidies.

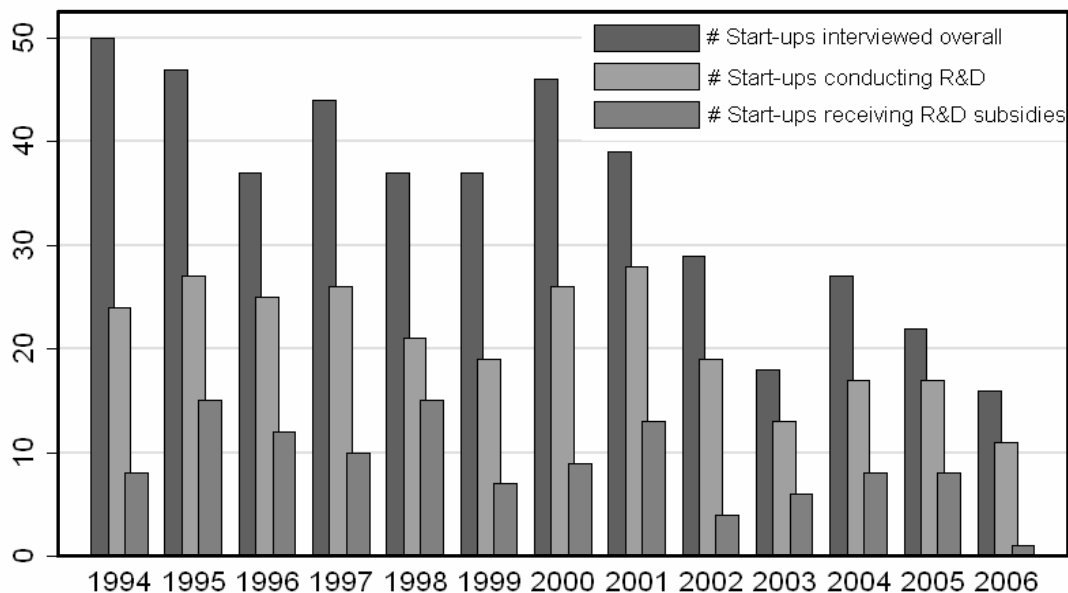


Figure 1: First business year of interviewed start-ups (overall), R&D-performing start-ups and those start-ups that received R&D subsidies.

Variables

We examine the effectiveness of R&D subsidies on employment growth and patent output, which are captured by the following variables:

Employment growth within the first three business years is defined as

$$Employment\ growth_{3\ business\ years} = \frac{Employment_{3rd\ year} - Employment_{1st\ year}}{Employment_{1st\ year}}$$

⁴ The Life-History-Calendar is a method developed by psychologists and sociologists and is based on the principles of the autobiographic memory. This means that – in a first step – we asked interviewees about the timing of well-known events (e.g. marriage, birth of children). In a second step, these events served as anchors for less well represented events (e.g. first interest in entrepreneurship).

⁵ Due to missing values for specific variables, 28 observations had to be dropped. Six of these start-ups did not survive the first three business years. Furthermore, two outliers were discarded which showed an employment growth of 5500% and 158 patent applications within the first four business years, respectively. We thus ended with 243 common observations, analyzed with regard to both outcome variables.

Here ‘Employment’ comprises different kind of employment relationships, such as the working time of founders, active partners, conventional employees, hired labor and trainees. The measure is normalized on full-time positions, thereby considering part-time jobs.

For the patent output, we accessed the database of the German patent information system (DEPATIS) provided by the German Patent and Trade Mark Office. For each interviewed start-up, we looked for patent applications where the founder(s) and/or partner(s) were named as inventors. Furthermore, we looked for patents which were applied for directly by the start-ups in our sample. This procedure captures potential patents of employees working for the start-ups. We then calculated the sum of patent applications in the years before the first business year as well as the sum of patent applications in each business year. Double counts resulting from co-patenting were eliminated. Our outcome variable covers the patent applications that can be attributed to the start-up’s R&D activity within the first three years.

Patents have been found to be applied in close temporal proximity to actual R&D activity (Hall et al. (1986)). Scherer (1984) provides survey evidence from the U.S. and the former West Germany suggesting a lag of nine months between the initial conception of an invention and the application for a patent. Therefore, we allow for a time lag of one year to capture patent applications that are still related to R&D activity of the first three business years. In short, the patent outcome can be depicted as follows:

$Patent\ output_{3\ business\ years} = P_{Founders} \cup P_{Partners} \cup P_{Start-ups}$ with

$$P_{Founders} = \sum_{t=1}^4 Patents\ of\ Founders_t, \quad P_{Partners} = \sum_{t=1}^4 Patents\ of\ Partners_t \quad \text{and} \quad P_{Start-ups} = \sum_{t=1}^4 Patents\ of\ Start-ups_t.$$

For the matching approach, our dataset allows us to base the conditional independence assumption on a broad set of variables which characterize the start-up before the first business year. We describe these variables in table 1.

Novelty	The <i>Novelty</i> of the business idea refers to the scope of the newness of the business idea. A Likert scale comprises no novelty (0), regional or local (1), supra-regional but national (2), European (3) and global novelty (4).
Academic spin-off	<i>Academic spin-offs</i> are start-ups where the business idea evolved from previous employment at a university or research institute. We code a start-up by a dummy variable with 1 in the case of an academic spin-off and with 0 otherwise.
Product	The value for the dummy variable <i>Product</i> is 1 if the start-up offered a product in the first three business years and the value is 0 in the case of service companies.
Team	<i>Team</i> start-ups were defined as venture set-ups where more than one person was actively involved in the founding process and was intended to become an owner of the company. We code a dummy variable with 0 in the case of a single founder, and with 1 in the case of a team start-up).
Patent stock	The patent stock is the sum of patent applications of founders and partners within five years before venture set-up. The variable is built up in the same way as the variable "patent output".
Target market	The scope of the <i>Target market</i> ranges from 0 to 3 – 0 denoting a regional or local target market, 1 denoting a supra-regional but national target market, 2 denoting a European market, and 3 indicating a global market.
Year 1994-1997 Year 1998-2001 Year 2002-2006	Dummy variables that capture the time of business start, i.e. the first business year of the company when accounting started either because of obligations from the commercial register or because of first revenues.
Nace 2..... Nace 3..... Nace 7..... Nace x.....	Industry-dummies (NACE, 1 digit): Chemical industry, metalworking industry, engineering Electrical engineering, fine mechanics and optics Information and Communication Technology, R&D, Services Miscellaneous

Table 1: Variables describing pre-treatment characteristics of the start-ups

The correlation matrix is given in table 2. Mean differences in the pre-treatment characteristics between subsidized and non-subsidized firms are depicted in the first column block of table 3.

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	Employment growth	Patent output	Take-up of R&D subsidies	Academic spin-off	Novelty	Patent stock	Product	Target market	Team	Year 1994-1997	Year 1998-2001	Year 2002-2006	Nace 2	Nace 3	Nace 7	Nace x
Employment growth	-															
Patent output	0.1169 *	-														
Take-up of R&D subsidies	0.1932 **	0.2155 ***	-													
Academic spin-off	0.1907 **	0.2725 ***	0.2268 ***	-												
Novelty	0.1278 **	0.3153 ***	0.2821 ***	0.2685 ***	-											
Patent stock	0.1243 *	0.5534 ***	0.1878 **	0.2835 ***	0.3510 ***	-										
Product	0.0639	0.2539 ***	0.1995 **	-0.0509	0.1965 **	0.1020	-									
Target market	0.1579 **	0.1415 **	0.0853	0.0765	0.2178 ***	0.1385 **	0.3151 ***	-								
Team	0.1373 **	0.0653	0.1404 **	0.2386 ***	0.0855	0.0914	0.0173	0.0677	-							
Year 1994-1997	-0.0113	0.0352	0.0172	-0.2193 *	-0.0990	-0.0053	0.0392	-0.1462 *	-0.0846	-						
Year 1998-2001	-0.0484	0.0118	0.0966	0.2500 *	-0.0162	0.0719	-0.0856	0.0149	0.0846	-0.5777 *	-					
Year 2002-2006	0.0647	-0.0513	-0.1233 *	-0.0298	0.1259 **	-0.0718	0.0495	0.1441 **	0.0012	-0.4717 ***	-0.4472 ***	-				
Nace 2	0.0419	-0.0287	0.0404	-0.1422 **	-0.0944	0.0377	0.2023 **	0.1442 **	0.0196	0.1182 *	-0.0971	-0.0246	-			
Nace 3	0.0694	0.2789 ***	0.1110 *	0.1027	0.2434 ***	0.1815 **	0.3119 ***	0.1253 *	0.0152	0.0919	0.0068	-0.1081 *	-0.3727 ***	-		
Nace 7	-0.0921	-0.1435 **	-0.0817	0.0960	-0.0634	-0.1120 *	-0.4089 ***	-0.1412 **	-0.0098	-0.1707 **	0.0983	0.0809	-0.4739 ***	-0.4546 ***	-	
Nace x	-0.0175	-0.1423 *	-0.0965	-0.0964	-0.1195 *	-0.1495 *	-0.1087 *	-0.1810 *	-0.0376	-0.0393	-0.0236	0.0685	-0.1967 ***	-0.1887 **	-0.2399 ***	-

Note: * p<.1; ** p<.05; *** p<.01

Table 2: Correlation matrix; N=243

	Before Matching		Employment growth After Matching		Patent output After Matching	
	Mean of...		Mean of matched...		Mean of matched...	
	... subsidised start-ups N=103	... non-subsidised start-ups (potential controls) N=140	... subsidised start-ups N=103	... non-subsidised start-ups (actual controls) N=139	... subsidised start-ups N=93	... non-subsidised start-ups (actual controls) N=140
Academic spin-off	0.2524	0.0857	0.2524	0.2382	0.1720	0.1572
Novelty	2.2913	1.3286	2.2913	2.2488	2.129	2.0703
Patent stock	1.6796	1.2143	1.6796	1.9601	1.5699	1.7291
Product	0.4563	0.2643	0.4563	0.2549	0.3979	0.4178
Target market	1.3884	1.2357	1.3883	1.3307	1.3656	1.489
Team	0.7670	0.6357	0.7670	0.7794	0.7527	0.6867
Year 1994-1997	0.3883	0.3714	0.3884	0.3095	0.4194	0.3364
Year 1998-2001	0.4078	0.3143	0.4078	0.3276	0.3763	0.2980
Year 2002-2006	0.2039	0.3143	0.2039	0.3629	0.2043	0.3656
Nace 2	0.3010	0.2643	0.3010	0.2320	0.3333	0.2891
Nace 3	0.3204	0.2214	0.3204	0.2512	0.2473	0.2982
Nace 7	0.3204	0.4000	0.3204	0.4270	0.3548	0.3406
Nace x	0.0583	0.1143	0.0583	0.0898	0.0645	0.0721
Employment growth	1.3101	0.8271	1.3101	0.7894	1.2829	0.8580
Patent output	3.5728	0.7571	3.5728	1.3373	2.7312	0.9632
Propensity score (employment growth)	0.4892	0.3758	0.4892	0.4827	-	-
Propensity score (patent output)	0.5031	0.3655	-	-	0.4664	0.4585

Please note: The balancing of the variables is depicted after kernel matching with the optimal bandwidth. Bold numbers indicate significant different means between observation from subsidized start-ups and non-subsidized start-ups before and after matching in a two-sided t-test (5%-significance level).

Table 3: Group differences between subsidised and non-subsidised start-ups before and after matching

4.2 ESTIMATION OF THE PROPENSITY SCORE AND COMMON SUPPORT

Table 3 shows that subsidized and non-subsidized firms exhibit significant differences regarding, e.g., the novelty of their business idea, the kind of business (product vs. service) and the origin of the business idea (academic spin-off). Subsidized start-ups are significantly more often team start-ups. This indicates that self selection into R&D support schemes and committee selection of program officials make the group of subsidized ventures a selective one. As a consequence, if the distinguishing characteristics of subsidized and non-subsidized firms have an impact on the outcome variable (employment growth and patent output, respectively), a direct comparison between the two groups will be biased. A priori the direction of the bias is unknown.

Consequently, those variables should be included in the estimation of the propensity score which influence both the receipt of R&D subsidies as well as the respective outcome variable. We estimate a propensity score model for each outcome variable. Therefore, we look for variables which

correlate with the receipt of R&D subsidies and simultaneously with the respective success measure (employment growth and patent output) (table 2). Moreover, we conduct multivariate analyses to identify other distinguishing characteristics between subsidized and non-subsidized firms which have an impact at the same time on employment growth and patenting, respectively. In the following, the variable choice for each propensity score model is explained.

Employment growth. Table 2 shows that the variables ‘Academic spin-off’, ‘Novelty’, ‘Patent stock’ and ‘Team’ are all correlated with both the take-up of R&D subsidies as well as employment growth. A high degree of novelty (which can be also seen in many prior patent applications), being an academic spin-off and a team start-up are all characteristics of innovative start-ups.⁶ At the same time, the positive correlation of these variables with the receipt of R&D subsidies points to a policy strategy of “picking the winners”.

The provision of products instead of services (variable ‘Product’) is correlated with the take-up of R&D subsidies but not correlated with employment growth. Apart from univariate statistics, we therefore run ordinary least squares regressions to determine whether the variable ‘Product’, particular founding years and the industry have an impact on employment growth. These regressions cannot reveal further determinants of employment growth.

Patent output. The variables ‘Academic spin-off’, ‘Novelty’, ‘Patent stock’ and ‘Product’ are all correlated with both the take-up of R&D subsidies as well as with patent output (table 2). Additionally, operating in electrical engineering, fine mechanics and optics (variable ‘Nace 3’) is positively correlated with the receipt of R&D subsidies and patent output. The patent applications, which are attributed to a start-up in each year, are highly correlated with one another, indicating path dependency of patent activity. We balance subsidized and non-subsidized firms on the basis of previous patent experience by introducing the number of patent applications in the last five years before founding (measured by the variable ‘Patent stock’) in the estimation of the propensity score. Since negative binomial regression models cannot display any further determinants of patent output, which also differentiate between subsidized and non-subsidized firms, we estimate the propensity score with the variables ‘Academic spin-off’, ‘Novelty’, ‘Patent stock’, ‘Product’ and the industry dummies.⁷

⁶ Our data is thus in line with Almus et al. (1999), who analyze the employment growth of start-ups in East Germany. They find that innovative start-ups grow on average faster than non-innovative start-ups.

⁷ The results from both multivariate analyses are available upon request from the authors.

The propensity to take up public R&D assistance is estimated with a logit model (table 4). Following the discussion above, the selected variables for each of the two models are regressed on the binary dependent variable ‘Take-up of R&D subsidies’. Since we are primarily interested in prediction and data reduction, redundancy and collinearity are of little account (Smith, 1997). However, this limits the interpretation of the coefficients, which are not further discussed here.

	Employment growth	Patent output
Dependent variable: Take-up of R&D subsidies		
Academic spin-off	0.8986 ** (0.4121)	1.2087 *** (0.4205)
Novelty	0.3186 *** (0.0865)	0.2796 *** (0.0899)
Patent stock	-0.0275 (0.0309)	-0.0322 (0.0314)
Product		0.7050 ** (0.3288)
Team	0.4301 (0.3115)	
Nace 2		0.4871 (0.5638)
Nace 3		0.3004 (0.5828)
Nace 7		0.1841 (0.5513)
Constant	-1.2822 *** (0.2957)	-1.4898 *** (0.5059)
N	243	243
LR chi2 (k)	(4) 28.48	(7) 35.02
Prob > LR	0.0000	0.0000
McFadden's R2	0.0860	0.1057
Note: * p<.1; ** p<.05; *** p<.01; standard errors in parentheses		

Table 4: Estimation of the propensity score

The common support condition ensures that any set of characteristics of subsidized firms (captured by the propensity score) can also be observed for non-subsidized ones. Especially for kernel matching, the condition of common support is important. Otherwise, non-subsidized firms that lack a potential matching partner are inevitably taken to construct the counterfactual. We determine the region of common support with a minimum-maximum comparison of the distribution of the propensity score. Figure 2 depicts the distribution of the propensity score for subsidized and non-subsidized firms. The region of common support is given by the overlap and requires discarding one non-subsidized (10 subsidised observations) from the analysis of employment growth (patent output).

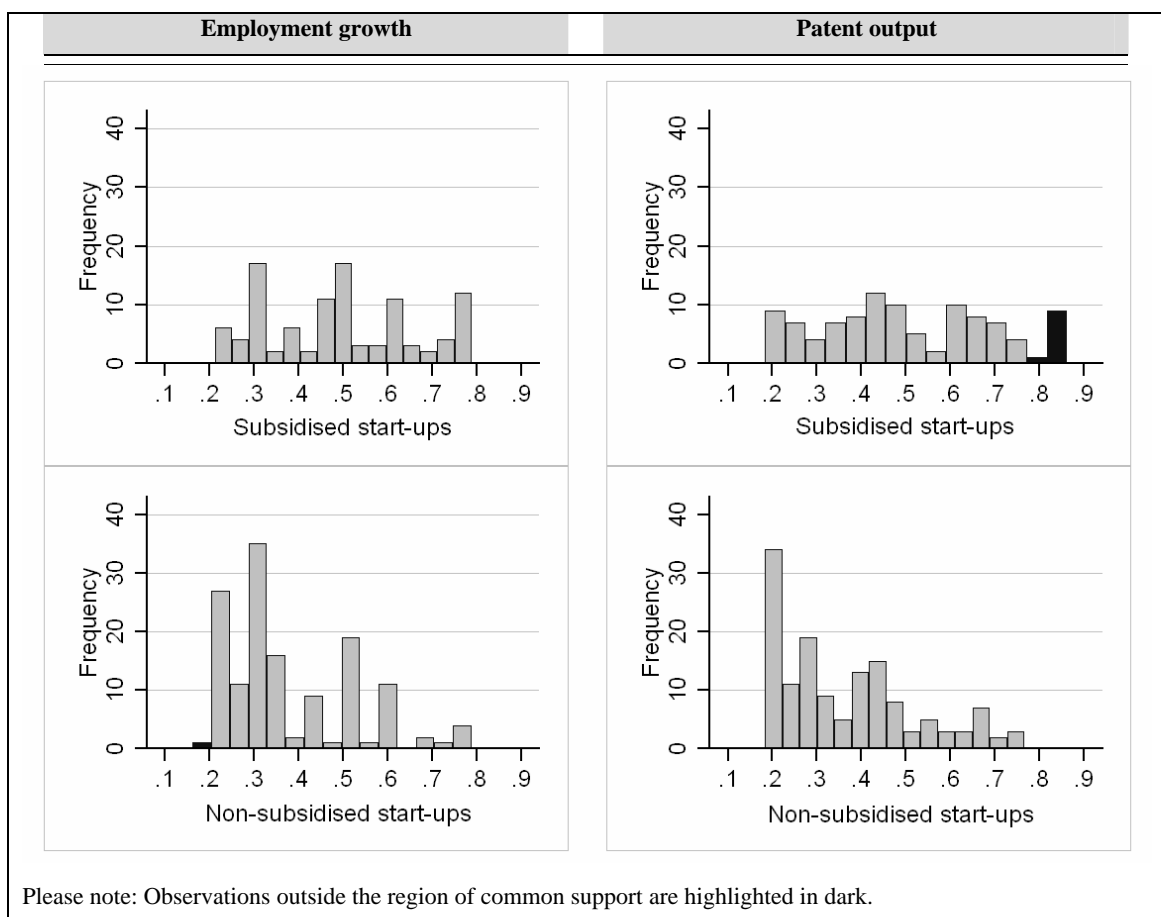


Figure 2: Distribution of the propensity score – separately for the analysis of employment growth (left column) and the analysis of the patent output (right column)

4.3 MATCHING AND MATCHING QUALITY

Calculating the optimal bandwidth for our sample, we arrive at $h = 0.0500$ for employment growth and $h = 0.0502$ for patent output⁸. We thus perform kernel matching employing a Gaussian kernel with a bandwidth of 0.0500 and 0.0502, respectively.⁹

The second and third column block of table 3 in the appendix show the characteristics of our control groups after matching. After matching, the non-subsidized and subsidized matched firms do not exhibit any significant differences regarding any characteristics which are assumed to have an impact on both, the receipt of R&D subsidies as well as on employment growth and patent output. Although industry dummies are not included in the propensity score estimation for the study of

⁸ The calculation is as follows. For the analysis of employment growth, $A = \min(0.166685, \frac{0.5259101 - 0.2990019}{1.34}) = 0.166685$ is inserted in $h = 0.9 \cdot A \cdot 242^{-\frac{1}{5}}$. Hence, the optimal bandwidth is $h = 0.0500$. Analogous to the previous calculation, the optimal bandwidth for the analysis of the patent output is derived by estimating $A = \min(0.1658171, \frac{0.5289473 - 0.2638597}{1.34}) = 0.11658171$ and

$h = 0.9 \cdot A \cdot 233^{-\frac{1}{5}} = 0.0502$.

⁹ Estimations are done using the psmatch2 Stata ado package by Leuven and Sianesi (2003) and the att Stata ado package by Becker and Ichino (2002).

employment growth, the matching procedure manages to equalize subsidized and non-subsidized firms in terms of their industry classification.

As recommended by Sianesi (2004), we re-estimate the propensity scores on the matched samples to compare the pseudo- R^2 s before and after matching. The pseudo- R^2 tells how well the variables that were included in the estimation of the propensity score explain the receipt of R&D subsidies. Before matching, the pseudo- R^2 should be high, and after matching fairly low. Moreover, a likelihood-ratio test of the joint insignificance of all the regressors before and after matching is performed. As required, the tests are rejected before but not rejected after matching.¹⁰

5. RESULTS AND THEIR ROBUSTNESS

The average treatment effect on the treated (ATT) (table 5) is the difference between the mean outcome of subsidized firms and matched non-subsidized firms. We use bootstrapping (200 replications) to calculate the standard error of the matching estimator.¹¹ The employment growth of subsidized start-ups exhibits an ATT of 0.5207, i.e. the difference between the mean employment growth of subsidized firms (=1.3101) and matched non-subsidized firms (=0.7894). In other words, R&D subsidies lead to an increase in employment growth of about 66%. The ATT turns out to be significant at the 0.01 significance level. Looking at patent applications, we note that subsidized firms show a more than 2.8 times higher patent output compared to their non-subsidized matched counterparts. This corresponds to an ATT of 1.7680, which is significant at the 0.05 level.

We employ other matching algorithms to estimate the sensitivity of the results on the employment of the kernel matching estimator¹². Table 5 shows that alternative bandwidth parameters for kernel matching, k-nearest neighbor matching, as well as radius matching¹³ yield qualitatively similar results. The estimates for the increase in employment growth range between 56% and 85%¹⁴. The patent output of subsidized start-ups is about 2.6 to 3.3 times higher. Our kernel estimates with the optimal bandwidth fit quite well in these ranges of estimates. Again, we check the matching quality analogous to the proceeding for kernel matching with the optimal bandwidth. The distribution

¹⁰ The test results are not depicted here, but can be obtained from the authors.

¹¹ Although a distribution theory for the cross-sectional and difference-in-difference kernel and local linear matching is derived in Heckman et al. (1998), standard errors for matching estimators are in practice generated using bootstrap resampling methods. The use of bootstrapping is backed by Abadie and Imbens (2008), who suggest that the standard bootstrap but can be applied to assess the variability of kernel or local linear matching estimators. However, they show that standard bootstrap resampling methods are not valid for assessing the variability of nearest neighbor estimators.

¹² See Caliendo (2006) for an overview of these matching algorithms.

¹³ Radius matching means that a subsidized start-up is matched to all non-subsidized firms within the caliper. The caliper is defined symmetrically and restricts the propensity score distance between the subsidized start-ups and the non-subsidized control units.

¹⁴ We do not consider the estimate from radius matching with caliper size 0.01 here, since it excludes 10 subsidized observations and is only significant at the 0.1 significance level.

of the covariates after matching, the pseudo- R^2 from logit estimation and the p-value of the likelihood-ratio test indicate a good matching quality for all these estimations.

	Matching algorithm	Mean outcome of matched		ATT	S.E.	# Observations	
		subsidised start-ups	non-subsidised start-ups			Sub-sidised	Non-subsidised
Employment growth	Kernel						
	Optimal bandwidth (=0.0500)	1.3101	0.7894	0.5207***	0.1892	103	139
	Bandwidth 0.02	1.3101	0.7983	0.5118**	0.2039	103	139
	Bandwidth 0.04	1.3101	0.7843	0.5258***	0.1728	103	139
	Bandwidth 0.06	1.3101	0.7971	0.5130***	0.1906	103	139
	Bandwidth 0.08	1.3101	0.8132	0.4969***	0.1898	103	139
	Bandwidth 0.10	1.3101	0.8244	0.4857**	0.2106	103	139
	K-NN						
	2 NN	1.3101	0.8220	0.4881	0.3178	103	139
	5 NN	1.3101	0.7066	0.6035**	0.2463	103	139
	10 NN	1.3101	0.7521	0.5580**	0.2358	103	139
	Radius						
	Caliper 0.01	1.2909	0.8544	0.4365*	0.2277	93	139
	Caliper 0.03	1.3022	0.8363	0.4660**	0.2158	102	139
	Caliper 0.10	1.3101	0.7711	0.5390**	0.2087	103	139
Patent output	Kernel						
	Optimal bandwidth (=0.0502)	2.7312	0.9632	1.7680**	0.8583	93	140
	Bandwidth 0.02	2.7312	0.8890	1.8421**	0.8321	93	140
	Bandwidth 0.04	2.7312	0.9474	1.7838**	0.7900	93	140
	Bandwidth 0.06	2.7312	0.9757	1.7555**	0.8628	93	140
	Bandwidth 0.08	2.7312	0.9849	1.7462**	0.8326	93	140
	Bandwidth 0.10	2.7312	0.9726	1.7585**	0.8101	93	140
	K-NN						
	2 NN	2.7312	0.7527	1.9785**	0.9115	93	140
	5 NN	2.7312	0.8882	1.8430**	0.8198	93	140
	10 NN	2.7312	0.8688	1.8624**	0.8541	93	140
	Radius						
	Caliper 0.01	2.5955	0.7903	1.8052**	0.8396	89	140
	Caliper 0.03	2.7312	0.8237	1.9075**	0.8600	93	140
	Caliper 0.10	2.7312	1.0201	1.7110**	0.8409	93	140
Note: * p<.1; ** p<.05; *** p<.01							

Note: * p<.1; ** p<.05; *** p<.01

Table 5: Overview of results obtained by different matching algorithms

Matching relies on strong untestable assumptions, particularly the conditional independence assumption. The validity of the conditional independence assumption relies crucially on the possibility to compare subsidized and non-subsidized firms on the basis of pre-treatment characteristics. Given our rich dataset, which concludes personal data of the founder and the founder team as well as characteristics of the start-up and the business idea, it is plausible to assume that the outcomes and the allocation of R&D subsidies are independent, conditional on observed attributes. Heckman et al. (1997) point out that matching methods substantially reduce biases when, first, all information is collected with the same questionnaire for both the subsidized and non-subsidized firms and, second, these are drawn from the same random sample (which is supported by the experimental evidence of Michalopoulos et al. (2004)). Both requisites are fulfilled in our dataset.

Moreover, the sample is considerably homogenous, since we only consider genuinely new start-ups in innovative industries in the Free State of Thuringia that were actually engaged in R&D.

Ten subsidised start-ups lie outside the region of common support (figure 2) and were thus excluded from the analysis of the patent output. For them, there are no potential matching partners, i.e. start-ups with similar pre-treatment characteristics that are not subsidized. Table 6 shows that these 10 subsidised start-ups outside the common support form a special group, even in the group of subsidized start-ups. They are different because they are all academic spin-offs that offer products in the field of electrical engineering, fine mechanics and optics (variable ‘nace 3’). Compared to matched subsidized start-ups, they differ significantly with regard to patent output, number of patents before founding and novelty of the business idea. They were significantly more often set up between 1998 and 2001. The outlier we had to exclude in the very beginning of the analysis (see footnote 5) follows the same pattern. It is another academic spin-off offering a product that constitutes a global novelty.

	Mean of subsidised firms outside common support (N=10)	Mean of subsidised firms inside common support (N=93)
Employment growth (3 business years)	1.5633	1.2828
Patent output (4 business years)	11.4	2.7312
Academic spin-off	1.0	0.1720
Novelty	3.8	2.1290
Patent stock	2.7	1.5699
Product	1.0	0.3978
Target market	1.6	1.3656
Team	0.9	0.7527
Year 1994-1997	0.1	0.4194
Year 1998-2001	0.7	0.3763
Year 2002-2006	0.2	0.2043
Nace 2	0.0	0.3333
Nace 3	1.0	0.2473
Nace 7	0.0	0.3548
Nace x	0.0	0.0571
Please note: Bold numbers indicate significant different means between subsidised firms inside and outside the region of common support (two-sided t-test, 5% significance level)		

Table 6: Characteristics of subsidised firms – inside and outside the region of common support

Our results are also backed by the self-report of windfall gains of the respective founders. We asked each founder of a start-up with subsidized R&D activity, “Would you have been engaged in R&D anyway?”. Only 19.2% answered “yes, readily”, 47.5% returned “yes, perhaps or on a reduced scale” and the remaining third (32.3%) said “no”. The latter two answer categories point to the additionality of R&D subsidies.

6. CONCLUSION

High-tech and high-growth start-ups take a pivotal role in innovation and entrepreneurship policies. Investigating the effectiveness of appropriate policy programs, our analysis provides evidence for the hypothesis of additionality of public R&D subsidies. Public R&D subsidies account for an employment growth 66% greater than without such intervention. Furthermore, subsidized start-ups have a 2.8 times higher patent output than their non-subsidized matched counterparts. These estimates take account of selection bias, which distinguishes ex-ante subsidized from non-subsidized firms. Our results are thus in line with Czarnitzki and Licht (2006), who also find additionality of public R&D schemes in East Germany. However, our analysis focuses on start-ups and thus suggests that newborn firms are capable of conducting additional R&D when they obtain public funds. R&D subsidies allow them to increase their R&D activity both in terms of additional employment and heightened patent applications. So our results conflict with the presumption that the research in start-ups cannot be scaled up since it is organized around a key researcher (or fixed research team, respectively) with a preassigned project scope.

Policy initiatives regularly focus on academic spin-offs, supposedly very effective in transferring knowledge from university or research institutes to industrial applications. This focus on academic spin-offs and its success can be nicely observed in our data. We had to exclude ten subsidized academic spin-offs from our analysis of the patent output — they all developed products and were outstanding in terms of the novelty of their business idea, so that we could not find any non-subsidized counterparts in the matching procedure. Hence, the observed funding academic of spin-offs can be regarded as policy success, since highly innovative start-ups are expected to offer the highest social benefits. However, these observations only stand out when the impact of subsidies on patent output is regarded. Their employment growth does not differ from other subsidized start-ups. This points to the early development of the spin-offs with respect to the marketability of their products.

Qualifying our result, we put forward a couple of limitations, which in turn point to future research opportunities. First, the quality of the patent applications which form the outcome variable patent output has not been considered. The patent quality determines crucially the social returns from the R&D activity. A lower patent quality in subsidized firms would put the higher quantity of patent applications in perspective. Public funds might pay the expenses for the patent applications of subsidized firms, so that they might be induced to file applications for low-value patents. Subsidized firms might also file for patents strategically, since patents serve as a justification to funding authorities. However, these are just presumptions which need empirical scrutiny.

Second, we define the receipt of R&D subsidies as a dummy variable, which thus accounts for heterogeneous intensity of public support. This limits our estimations to overall qualitative

results. Although our approach of taking an aggregate view on the subsidy environment has its merits when looking at the almost bewildering range of support schemes, a more detailed look at the design of support schemes is needed for more precise policy recommendations.

Third, we focus on those start-ups that conduct R&D within the first three business years. While this restriction allows us to match subsidized and non-subsidized start-ups in a very homogeneous sample, it neglects the potential impact of R&D subsidies in inducing firms to conduct R&D at all.

Fourth, the most general limitation to our analysis is probably the SUTVA and the restriction to short-term private returns. However, we analyze two outcome variables in different stages of the innovation process, which makes us confident that we can tentatively infer from the additional R&D effort (proxied by employment growth) to additionally generated knowledge (captured by patents) and finally to social benefits reached by knowledge spillovers and market effects. Moreover, the neglect of interactions between subsidized and non-subsidized firms and a missing proxy for social returns, although in line with the concurrent literature, should motivate further research.

In view of our result suggesting a high and positive impact of R&D policy schemes on start-up performance, the effective selectivity of these schemes requires a more fundamental question about R&D subsidies to start-ups. The economic rationale for R&D subsidies is to facilitate R&D projects that are privately not profitable, but yield at the same time social returns in excess of the opportunity cost of capital. However, the identification of social benefits should be as difficult for policy makers and program officials as for evaluation studies such as this one. In addition to that, Lerner (1999) points to public choice considerations which cast doubt on policy makers' and program officials' incentives to fund marginal projects. They are rather inclined to support projects that are likely winners, so that they can credit themselves with the success of subsidized start-ups, even though their marginal contribution might be small. For our analysis, we cannot exclude those effects, as we use only variables indicating private returns. However, on this basis, the selection bias seems to be weak since, on the one hand, the support of the propensity scores for the subsidized and non-subsidized firms overlap to a very high degree (figure 2), while on the other hand, in a companion study (Cantner and Kösters, 2009) we find that selectivity is mainly based on novelty and the availability of appropriate programs (favouring start-ups, product start-ups, team start-ups).

In addition, the sheer enormity of subsidization (remember that 42.6% of R&D-performing start-ups receive public R&D funds in our sample) points to likely market distortions. This generous availability of public R&D funds may thwart the development of a market for private R&D funding. In this way, the fact of existing subsidies is the rationale for the need of ongoing subsidisation.

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