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Evaluation of Public R&D Policies: A Cross-country Comparison

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Non-technical summary

Technological change is an important determinant of long-run productivity which is essential for securing competitiveness both at the firm-level and for the economy as a whole. Public authorities expect that increasing R&D investment causes intensified technological progress and finally accelerates growth in the long-run. In this line, countries cannot merely rely on public R&D (i.e. conducted by universities or public research centres), but they have to make sure that R&D is also performed at business level. In order to stimulate these private R&D activities, governments usually offer a wide range of public incentives like R&D subsidies, tax credits, technological consultancy etc.

In this paper, we empirically evaluate whether public support for innovation spurs investment at the firm level. Conducting a treatment effects analysis, we investigate whether public R&D funding crowds out private investment in the business sector and whether the government could further foster R&D by supporting currently non-subsidized firms. The analysis is based on harmonized micro data from the 4th wave of the Community Innovation Survey (CIS4) covering the years 2002 – 2004 of Belgium, Germany and Luxembourg, as well as a CIS-harmonized survey from South Africa, and Spanish data from the Panel de Innovación Tecnológica (PITEC) of the year 2004. In addition, we also test for possible misallocation of public funds.

Our sample concerns only innovative firms and covers manufacturing as well as business related services sectors. In total, the sample consists of 9790 observations of 5 different countries, out of which 3854 received R&D subsidies. Using a non-parametric nearest-neighbor matching, we find that firms that received subsidies would have invested significantly less in R&D and innovation if they would not have received public support. Full crowding-out can thus be ruled out for all the countries of our sample. On similar grounds, when estimating the treatment effect on the untreated, we find that untreated firms would on average invest significantly more if they would receive subsidies. With the exception of one country, all countries of our sample would thus benefit from extending existing innovation policies to currently non-subsidized firms. Finally, these two matching results, i.e. the treatment on the treated and the treatment on the untreated, can be combined in order to test for misallocation of public funds. Misallocation of public funds would be present if the treatment effect of the untreated was significantly larger than the treatment effect on the treated. Our analysis does not uncover any systematic misallocation of public funding for the countries under review, though.

Das Wichtigste in Kürze

Technologischer Wandel ist ein wichtiger Faktor, um langfristig sowohl auf der Unternehmensebene wie auch auf makroökonomischer Ebene die Wettbewerbsfähigkeit zu sichern. Es wird im Allgemeinen erwartet, dass Forschung und Entwicklung (FuE) in hohem Maße zu technologischem Fortschritt beiträgt und das Wachstum einer Volkswirtschaft beschleunigt. Daher verlassen sich Regierungen in der Regel nicht nur auf öffentlich durchgeführte FuE-Aktivitäten, sondern versuchen ebenso private Investitionen in FuE zu stimulieren. Üblicherweise kommen dazu eine Reihe von Maßnahmen zum Einsatz, z.B. direkte Subventionen, steuerliche Anreize für FuE-Aktivitäten sowie technologische Beratung.

In dieser Studie evaluieren wir empirisch, (i) inwieweit direkte öffentliche FuE-Förderung zu Additionalität auf der Unternehmensebene führt, (ii) ob der FuE nicht-geförderter Firmen Subventionen ebenfalls zu Gute gekommen wären, und (iii) werden in einem letzten Analyseschritt die beiden ersten Resultate genutzt, um mögliche Ineffizienzen im Fördervergabeprozess aufzudecken. Dazu werden Daten des „Community Innovation Surveys" (CIS) aus Belgien, Deutschland und Luxemburg verwendet. Zusätzlich stehen CIS-harmonisierte Informationen aus Südafrika zur Verfügung, sowie Daten des „Panel de Innovación Tecnológica (PITEC)" aus Spanien.

Insgesamt umfasst die Stichprobe 9790 Beobachtungen innovativer Unternehmen des Produzierenden Gewerbes sowie unternehmensnahen Dienstleistungssektoren. Unter Verwendung eines nicht-parametrischen Matching-Schätzers zeigt sich, dass subventionierte Unternehmen mehr in FuE investieren als in der kontrafaktischen Situation ohne Förderung. Die Schätzung einer kontrafaktischen Situation für nicht-geförderte Unternehmen zeigt auch, dass diese im Durschnitt mehr in FuE investiert hätten, wenn Subventionen an sie vergeben worden wären. Werden die beiden Schätzresultate im Vergleich gesehen, kann ein Test auf potenzielle Ineffizienzen im Vergabeprozess der öffentlichen Mittel durchgeführt werden. Ineffizienzen lägen vor, wenn nicht-geförderte Firmen signifikant mehr in FuE investiert hätten, wenn sie gefördert worden wären, als die Unternehmen die tatsächlich Subventionen erhalten hätten. Die Tests zeigen jedoch, dass in keinem der untersuchten Länder derartige Ineffizienzen nachgewiesen werden können. Jedoch stellt sich mit den vorliegenden Daten und der angewandten Schätzmethodik auch heraus, dass die tatsächliche Fördervergabe im Durchschnitt nicht zu mehr Investitionen führt, als eine hypothetische Vergabe an nicht-geförderte Firmen.

Evaluation of public R&D policies: A cross-country comparison*

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Abstract

This study focuses on the effect of public funding on internal R&D investment and on total innovation intensity on a cross-country comparative level. Using harmonised micro data from five different countries, this study analyzes the heterogeneity of the use of policy instruments. Applying a nonparametric matching method to identify the treatment effect, we find that on average firms would have invested significantly less if they would not have received subsidies. On similar grounds, our estimation also takes into account the "treatment effects on the untreated". This estimation enables us to assess whether or not governments could further foster R&D activities by extending innovation policies to currently not supported firms. With the exception of one country, all the governments of the sample would benefit from an extension of their subsidy policies. Finally, these two matching results can be combined in order to test for misallocation of public funds. Our analysis does not uncover any systematic misallocation of public funding for the countries under review.

Keywords: Innovation, Policy Evaluation, Treatment Effects, Cross-country comparison
JEL-Classification: O38

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1. Introduction

Technological change is an important determinant of long-run productivity, essential for securing competitiveness both at the firm-level and at the macro level (Aghion and Howitt, 2005, Jones, 2005). However, investment in R&D suffers from market failure such that the socially optimal investment level is larger than the level of private investment because of external effects (Arrow, 1962). Therefore, many countries subsidize R&D in order to close the gap between private and social equilibrium. Public authorities expect that increasing R&D investment causes intensified technological progress and finally accelerates growth in the long-run. Although R&D subsidy schemes have been evaluated frequently (see David et al., 2000, Klette et al., 2000, Cerulli, 2010), this study will contribute to the existing literature by investigating the effects of R&D subsidies in five countries of different size, different factors of endowments and different innovation policies.

Using harmonized micro data from the 4th wave of the Community Innovation Survey (CIS4), covering the years 2002 – 2004 of Belgium, Germany and Luxembourg, as well as a CIS-harmonized survey from South Africa, and Spanish data from the *Panel de Innovación Tecnológica* (PITEC) of the year 2004, allows a large scale study on the effects of innovation policies on total innovation intensity and internal R&D investment in these five countries. As a matter of fact, one would expect that the optimal policy mix varies across countries with different industry structures. Belgium as small open economy possibly applies different innovation policies than South Africa and these countries may put a different emphasis on policy goals. Furthermore, Germany as large economy with strong manufacturing industries, as well as Eastern Germany still regarded as transition economy, certainly requires different policy instruments than Luxembourg with strong focus on financial services.

Although many aspects of the impact of subsidies on R&D and innovation have been investigated at length in scholarly literature, it remains difficult to draw ultimate conclusions from a bundle of studies that use data from different countries, different data sources, and different methods (see e.g. David et al., 2000). Our study thus has the advantage that we can draw conclusions where possible heterogeneous results are stemming from actual differences across countries and do not result from heterogeneity in the data collection.

A further feature of this study consists in the inclusion of an emerging country, South Africa, and a transition economy (Eastern Germany). Even though recent literature expresses a growing interest in the matter (see e.g. Garcia and Mohnen, 2010; Vertesy and Szirmai, 2010; Ramani and Mukherjee, 2010, Hall and Maffioli, 2008) not many comparable results between industrialized and emerging (or developing) economies have been obtained so far.

As common in the literature, we are mainly interested in estimating the "treatment effect on the treated". In other words, we are interested to know how much a firm would have invested if it would not have received subsidies. Thus, we investigate whether public R&D funding stimulates private R&D and innovation activities or whether we face crowding-out effects and firms just substitute public means for private investment. However, an interesting contribution to the literature by this study is that we also analyse the so-called "treatment effect on the untreated", which is much less commonly done. This effect allows an estimation of what companies that did not receive a subsidy would have invested if they would have gotten support. Finally, the combination of the two estimations allows testing for possible misallocation of public funds as we will outline below.

The remainder of the paper is organized as follows. The second section briefly reviews some recent literature, section three outlines the econometric methods used in the study and the fourth section introduces the data sources and variables employed in the analysis. Section five presents the empirical results and the final section concludes.

2. This study in the context of existing literature

Over the last years, a great bulk of literature has emphasised the importance of business R&D in fostering innovation, technological change and economic growth (Romer, 1990). Even though the "public good attribute" of knowledge as well as the well known market failures towards R&D investment are valid justifications for governmental intervention, it is crucial for policy-makers to be able to evaluate whether or not their policies achieve the desired effect (i.e. an extension of innovation activities because of public financing and not a mere crowding out of private R&D investment). In this vein, the impact of R&D policies on firms' innovation behaviour has been of interest in the economic literature for years. David et al. (2000) survey micro and macroeconomic studies on that topic. One major result of their survey is that most of the estimations reviewed are subject to a potential selection bias as recipients for subsidies might be chosen by the government because they are more promising candidates in succeeding their research projects. In this case, funding becomes endogenous to innovative activity, leading to bias in regressions of e.g. R&D intensity on government subsidies. More recent studies addressing the selection bias include Busom (2000), Wallsten (2000), Lach (2002), Czarnitzki and Fier (2002), Almus and Czarnitzki (2003), Duguet (2004), González et al. (2005), Hussinger (2008) and Cerulli and Potí (2008, 2010). Other microeconomic approaches take different output measures into consideration. Examples include the effects of subsidies on patent applications, productivity, fixed-asset investment, returns on sales and growth of sales or employment (see Klette, Moen and Griliches (2000) for a comprehensive survey). However, no clear cut results come out of these studies and the amount of crowding out, if any, differs from one analysis to another. Finally, Cerulli (2010) reviews the principle econometric models used to measure the effects of public support on R&D investment. The author offers a comprehensive overview on the subject by presenting a taxonomy, classifying papers according to their estimation methods, the type of data and the type of policy variable.

In this vein, our study focuses on the effect of public funding on internal R&D investment and on total innovation intensity on a cross-country comparative level. Undeniably, the countries of our analysis present heterogeneous industry structures. Belgium is mainly an export-oriented economy. In terms of export per capita, Belgium is the world's leading export country. This modern, private-enterprise economy capitalizes on its central geographic location, highly developed transport network, and diversified industrial and commercial base with its main industries concentrated in the Flemish area in the north of the country. Germany, the fifth largest economy in the world (in purchasing power parity terms) and Europe's largest, is a leading exporter of machinery, vehicles, chemicals, and household equipment and benefits from a highly skilled labour force. The modernization and integration of the Eastern German economy – still considered a transition economy where the number of producing firms remains far below the average of that of Western Germany - explains why subsidies are still much higher in this part of the country. As far as Luxembourg is concerned, even though the country's economic take-off was due to the discovery of iron ore around 1850, its economy is nowadays mainly characterised by its prominent international financial centre, ranking eighth among the largest financial centres worldwide and accounting for about 28% of the country's GDP. With regards to Spain, though most of the country's active population works in the tertiary sector (a bit more than 60%), Spain counts among the biggest car producers on the market. Besides holding the biggest fishing fleet of the EU, it is also a large exporter of steel, chemicals and clothing and one of the most important producers of olive oil. Finally, South Africa - a middle-income, emerging market - is the economic powerhouse of

Africa. While the country presents modern infrastructure, good communication networks and a stock market ranked 17th largest in the world, its economy is above all characterised by its abundant supply of natural resources, leading the continent in industrial output and mineral production.[1]

In this context, the present study complements the existing literature in mainly two aspects: (1) we analyse the effects of public subsidies in the context of these highly heterogeneous economies. Compared to most existing studies where no clear-cut comparative results could be found, our estimation presents the advantage of allowing for comparable conclusions. Based on harmonized data, the estimation allows concluding that different findings come from actual differences in the use of public policies (e.g. "picking the winner" vs. "aiding the poor" strategies) and not because of different data collection methods. (2) Our estimation takes into account the "treatment effects on the untreated". Not frequently done in the literature so far, this estimation enables investigating whether or not governments could further foster R&D activities by extending innovation policies to currently not supported firms in order to accelerate technological progress and long-term growth. In addition, the combination of both treatment effects allows detecting possible misallocations of public resources.

3. Econometric Method

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

[1] The "stylized facts" about the different countries mentioned in this paragraph were obtained from various sources; among others the World Banks' *World Development Indicators*, CIA's *World Factbooks* and the OECD's *Economic Survey* series of our respective countries.

estimation strategies to correct for selection bias (see Heckman et al., 1999, Imbens and Wooldridge, 2009, for surveys) including the difference-in-difference estimator, control function approaches (selection models), instrumental variable (IV) estimation and non-parametric matching. The difference-in-difference method requires panel data with observations before and after (or while) the treatment (change of subsidy status). As our database (to be described in the following subsection) consists of cross-sections from different countries, we cannot apply this estimator. For the application of IV estimators and selection models one needs valid instruments (or an "exclusion restriction" in the selection model case) for the treatment variables. It is very difficult in our case to find possible candidates being used as instruments. Hence, the most appropriate choice is the matching estimator for our data. Its main advantage over IV and selection models is that we neither have to assume any functional form for the outcome equation nor is a distributional assumption on the error terms of the selection equation and the outcome equation necessary. The disadvantage is that it does only control for selection on observables, that is, one assumes that there is no unobserved factor driving the program participation. If panel data were available, one could at least control for unobserved heterogeneity which is constant over time. As we have to rely on a single cross-section of data, we have to maintain the assumption that we observe all important determinants of the subsidy receipt. This is a clear limitation when only cross-sectional data is available.

Matching estimators have been applied and discussed by Angrist (1998), Dehejia and Wahba (1999), Heckman et al. (1997, 1998a, 1998b), and Lechner (1999, 2000), among others. Matching directly addresses the question "What would a treated firm with given characteristics have done if it had not been treated?" A treatment in our context is the receipt of innovation subsidies. Those observations on treated firms are compared with a selected group of non-treated firms with similar characteristics (not with all non-recipients). Our fundamental evaluation question can be illustrated by an equation describing the average treatment effect on the treated individuals or firms, respectively:

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

where Y^T is the outcome variable. We will consider various measures of innovation in the subsequent empirical analysis. The status S refers to the group: S=1 is the treatment group and S=0 the non-treated firms. Y^C is the potential outcome which would have been realized if the treatment group (S=1) had not been treated. The problem is obvious: while the outcome of the treated firms in case of treatment, $E(Y^T|S=1)$, is directly observable, it is not the case for the counterpart. This is defined as the basic problem of causal inference (Holland, 1986). What would these firms have realized if they had not received the treatment? $E(Y^C|S=1)$ is a counterfactual situation which is not observable and, therefore, has to be estimated. In the case of matching, this potential outcome of treated firms is constructed from a control group of firms that did not receive innovation subsidies. The matching relies on the intuitively attracting idea to balance the sample of program participants and comparable non-participants. Remaining differences in the outcome variable between both groups are then attributed to the treatment.

Initially the counterfactual cannot simply be estimated as average outcome of the non-participants, because $E(Y^C|S=1) \neq E(Y^C|S=0)$ due to the possible selection bias. The participant group and non-participant group are expected to differ, except in cases of randomly assigned measures in experimental settings. Rubin (1977) introduced the conditional independence assumption (CIA) to overcome the selection problem, that is, participation and potential outcome are independent for individuals with the same set of exogenous characteristics X. Thus, the critical assumption using the matching approach is whether we can observe the crucial factors determining the entry into the programme. If this assumption is valid, it follows that

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

The outcome of the non-participants can be used to estimate the counterfactual outcome of the participants in case of non-participation provided that there are no systematic differences in the observed characteristics between both groups. The treatment effect can be written as

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

Conditioning on *X* takes account of the selection bias due to observable differences between participants and non-participants. In our case, we conduct a Nearest Neighbor matching, that is, for each treated firm we pick the most similar firm from the potential control group of non-subsidized firms. In addition to the CIA, another important precondition for consistency of the matching estimator is common support, i.e. it is necessary that the control group contains at least one sufficiently similar observation for each treated firm. In practice, the sample to be evaluated is restricted to common support. If the overlap between the samples is too small, the matching estimator is not applicable.

As one often wants to consider more than one matching argument, one has to deal with the "curse of dimensionality". If we employ a lot of variables in the matching function, it will become difficult to find appropriate controls. Rosenbaum and Rubin (1983) suggested to use a propensity score as a single index and thus to reduce the number of variables included in the matching function to just one. Therefore a probit model is estimated on the dummy indicating the receipt of subsidies *S*. The estimated propensity scores are subsequently used as matching argument. Lechner (1998) introduced a modification of the propensity score matching ("hybrid matching") as one often wants to include additional variables, e.g. like firm size, directly in the matching function. In this case, instead of a single X (the propensity score), other important characteristics may be employed in the matching function. The matching protocol in Table 1 summarizes the empirical implementation of the matching procedure used in this paper.

Table 1: 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	Calculate the Mahalanobis distance between this firm and all non-subsidized firms in order to find the most similar control observation. $MD_{ij} = \left(Z_j - Z_i\right)' \Omega^{-1} \left(Z_j - Z_i\right)$ where Ω is the empirical covariance matrix of the matching arguments based on the sample of potential controls. If only the propensity score is used, there is no need to calculate a multidimensional distance. In that case, e.g. a Euclidian distance is sufficient.
Step 5	In this application of the matching, we restrict the group of potential neighbors to firms active in the same industry as the particular treated firm. Select the observation with the minimum distance from the remaining sample. (Do not remove the selected controls from the pool of potential controls, so that it can be used again.)
Step 6	Repeat steps 3 to 5 for all observations on subsidized firms.
Step 7	Using the matched comparison group, the average effect on the treated can thus be calculated as the mean difference of the matched samples: $$\hat{\alpha}_{TT} = \frac{1}{n^T}\left(\sum_i Y_i^T - \sum_i \widehat{Y_i^C}\right)$$ with $\widehat{Y_i^C}$ being the counterfactual for i and n^T is the sample size (of treated firms).
Step 8	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.

The calculation of the "treatment effect on the untreated" is analogous to the method outlined above. In this case, one searches for twins of the non-subsidized firms in the group of subsidized firms (see e.g. Lechner and Gerfin, 2001, for more details).

4. Data and variables

The data used in this paper stem from various sources. The firm level data of Belgium[2], Germany[3] and Luxembourg come from the Community Innovation Survey (CIS4) and refer to the years 2002 to 2004. The CIS covers most EU member states, Norway and Iceland using a largely harmonized questionnaire throughout participating countries. Eurostat presents detailed descriptive survey results for all countries and aggregate statistics. South Africa, like more and more emerging and developing countries, introduced an innovation survey aligned on the European CIS. This survey is conducted by the Centre for Science, Technology and Innovation Indicators (CeSTII), established to undertake regular national R&D and innovation surveys on behalf of the Department of Science and Technology (DST) and to produce national indicators from the survey results to provide inputs for policy makers and a basis for international comparisons. The CIS databases contain information on a cross-section of firms active in the manufacturing sector and in selected business services.

The data from Spain stem from the *Panel de Innovación Tecnológica* (PITEC). Initiated in 2004 with the aim of improving the availability of statistical information on technological change and innovation activities in Spanish companies, PITEC is the fruit of the joint effort of the National Institute of Statistics (INE), the Spanish Foundation for Science and Technology (FECYT) and the Cotec Foundation[4].

Our sample concerns only innovative firms and covers manufacturing as well as business related services sectors. In total, the sample consists of 9790 observations of 5 different countries, out of which 3854 received R&D subsidies. According to the 3rd edition of the Oslo Manual – which is the definition followed by the CIS - an innovative firm is one that has

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[2] The data of Belgium concerns only Flanders, the Flemish part of the country.

[3] For Germany, we split the sample into two parts, Eastern and Western Germany. For the rest of the paper, those two regions will be analyzed and evaluated separately.

[4] The data is available online: http://icono.fecyt.es/contenido.asp?dir=05)Publi/AA)panel.

implemented an innovation during the period under review. An innovation is defined as the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations (see Eurostat and OECD, 2005).

The receipt of subsidies is denoted by a dummy variable equal to one for firms that received public R&D funding over the period 2002 to 2004 and zero otherwise. No difference is made between the various subsidy programmes. They include national R&D subsidies from the governments of the respective countries of our sample as well as EU financing schemes. As this variable covers a three year period for the countries for which we use CIS4 data, we use values of 2002 for the covariates in order to avoid endogeneity problems. For Spain, we use lagged values of the covariates measured before 2004 whenever possible for the same reason.

As outcome variables, we consider the total innovation intensity, *INNOV_INT*, at the firm level in 2004, which is the ratio of total innovation expenditure to sales (multiplied by 100), as well as the internal R&D investment, *INT_RD_INT*, being the ratio of internal R&D expenditures to sales (multiplied by 100)[5].

We use several control variables in our analysis that might have an impact on whether or not a firm receives public subsidies. As the same variables were not always available for all the countries of our sample, some of the control variables differ from one country to the other.

The log of the firm's age (*LNAGE*) is included in the analysis as it is often claimed that older firms are more reluctant to pursue innovation and as a consequence they might be less likely to apply for public research subsidies. The log of the number of employees (*LOGEMP*) takes into account possible size effects. As mentioned before, in order to avoid the concern of potential endogeneity due to the correlation of the receipt of subsidies and increasing the

[5] The CIS definition of R&D expenditure follows the Frascati Manual (OECD, 1993).

number of employees, we use the number of employment of 2002 and R&D and innovation expenditure of 2004.

Further we include a dummy variable to capture whether a firm is part of a group (*GP*), and if so, whether or not its headquarters are on national or foreign territory (*FOREIGN*). Firms that belong to a group with the parent company on national territory might be more likely to receive subsidies because they presumably have better information about governmental programmes due to their network linkages. In their decision making process, governments might favour firms that are part of a group because of potential spillover effects and specialised know-how national entities might have from their foreign branches. However, firms belonging to groups with a foreign parent company might be more likely to file applications in their home country. In addition, governments typically maintain special policy instruments for small and medium-sized firms. If a small firm, however, is majority-owned by a large parent company, it would no longer qualify for most SME-programs and hence the likelihood to receive a subsidy is reduced. The dummies *GP* and *FOREIGN* thus also control for this type of company profile, and a-priori it is unclear whether the effect is positive or negative because of the two opposing arguments outlined above.

Usually it is desirable to control for the capital intensity of firms in order to control for different technologies used in the production process. As a matter of fact, companies with capital-intensive production might rely more heavily on innovation activities than labour-intensive firms. Furthermore, capital may serve as collateral in credit negotiations with potential lenders, facilitating access to external sources of financing. Such firms are thus more likely to already have more experience in conducting R&D and innovation activities than firms that faced financial constraints in the past. Unfortunately, we do not have information about firms' capital stock for most countries. However, we can use lagged investment into tangible assets as a proxy variable. We define *KINT* as the ratio of investment into tangible assets divided by the number of employees. For South Africa, we do not have any information, and thus cannot account for this variable. For Flanders, there are many missing values for the investment variable. Instead of imputing these missing values with the help of a mean or of information of other years, we created a dummy variable (*d(kint = missing)*) that takes on the value 1 if the value for the investment is missing. Once we include this dummy in the analysis, we can impute, for instance, a zero for the missing in the investment variable and the dummy will capture the bias arising from this transformation in the estimated slope of the investment variable.

To control for technological prowess or previous R&D experience, the analysis includes a dummy variable indicating whether firms have permanent, internal R&D activities (*PERM_RD_INT*). Finally, we include an export dummy (*EXPORT*) to capture whether a firm faces foreign competition. Such firms may be more innovative and more likely to apply for subsidies as they may have more competition than firms only serving the domestic market. Table 2 shows the descriptive statistics of the variables of our sample.

[Insert Table 2, descriptive statistics, about here]

As the t-tests show, there are some significant differences between the subsidized and the non-subsidized firms. For all the countries but Eastern Germany, the subsidized firms are larger than the non-subsidized ones. With the exception of Luxembourg and Eastern Germany, subsidized firms tend to be more capital-intensive. For Flanders and Germany (East as well as West), we can observe a significant difference in export activities between the treated and the untreated groups. More importantly, in all the countries of our sample, the subsidized firms have significantly more permanent internal R&D activities than the non-subsidized firms as well as – with the exception of Luxembourg - higher total innovation and internal R&D expenditure. We thus can suspect that governments adopt a "picking-the-winner" strategy, favouring the firms that invest more substantially in R&D and innovation and look thus like more promising candidates than others. Luxembourg appears to be an exception, given that on average internal R&D expenditures and total innovation intensity are not significantly different among the two groups of firms. With the exception of Eastern Germany, the age of the firm does not seem to differ between treated and non-treated groups. Finally, being part of a group or having the parent company abroad does not significantly differ between the subsidized and the non-subsidized firms (expect for the group variable in Spain).

5. Econometric Results

Before applying the matching methodology, we present the probit models on the likelihood to receive subsidies. These models are used to obtain the propensity score which is employed as matching argument subsequently. The results of the probit estimations on the receipt of subsidies are presented in table 3. As already indicated by the descriptive statistics, size, export, capital intensity and permanent internal R&D are the most important variables driving the selection in most countries.[6] The estimation additionally shows that for the countries where this variable is significant (Flanders and Spain), a firm with a foreign parent company is less likely to receive subsidies than other firms. The same is true for Spanish firms that are part of a group.

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[6] At this stage, it has to be noted that the employment variable for Spain cannot be interpreted in the same straightforward way as for the other countries of the sample. For reasons of opportunity and viability, PITEC started with two samples with data from 2003: a sample of firms with 200 or more employees (sample of big firms (MEG), which represented 73% of all firms with 200 or more employees according to data from the DIRCE), and a sample of firms with intramural R&D expenditures (MID). Given the improvements made by the INE in information on firms undertaking R&D activities, there were enlargements of the second sample in 2004 and 2005. Moreover, in 2004, a sample of firms with fewer than 200 employees, external R&D expenditure and no intramural R&D expenditure (MIDE); and a representative sample of firms with fewer than 200 employees and no innovation expenditure (MEP) were included. For further detail, see http://icono.fecyt.es/05)Publi/AA)panel/bdPITEC_June2010_ing.pdf.

[Insert Table 3, Probit estimations, about here]

Table 4 presents the results of the matching by propensity score.[7] As the means and corresponding t-tests show, our sample is well balanced according to all employed covariates after the matching. There are no statistically significant differences in the exogenous variables. However, with regards to the outcome variables, significant mean differences exist after the matching. Those can be attributed to the treatment and full crowding-out with regard to public funding can hence be rejected. As a consequqnce, on average, the subsidised firms would have invested significantly less in R&D and innovation if they would not have been subsidized. The fact that after the matching significant mean difference exists between the treated and the non treated group in Luxembourg (and that this difference was not significant before the matching) might indicate that the Luxembourgish government follows an "aiding-the-poor" strategy rather than a "picking-the-winner" one. However, it could also signify that the government privileges national over foreign firms, as indicated by the negative sign of the *FOREIGN* variable in the probit regression[8]. Tables A.7 and A.8 in the appendix display OLS regressions for internal R&D intensity and total innovation intensity. One can see that the OLS estimates are comparatively similar to the matching in this case.

[Insert Table 4, matching results: treatment on the treated, about here]

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[7] In two cases, the propensity score matching did not balance the samples in all covariates. Therefore, we applied hybrid matching by including additional arguments in the matching function (see Lechner, 1998). For Western Germany, the matching has been done by propensity score and *LNAGE*. For Flanders, it has been done by propensity score, *FOREIGN* and 2 industry dummies.

[8] The non-significance of this variable in the Probit regression might be attributable to the relatively small size of the sample.

Table 5 displays the results of the treatment effects on the untreated. As for the matching results on the treated, the means and t-statistics of the matching on the untreated show that all the covariates of our sample are well balanced after the matching. As for the outcome variables, significant mean differences exist after the matching (with the exception of South Africa). Those differences can be attributed to a lack of treatment. In other words, with the exception of South Africa, all the countries of the sample would possibly benefit from an extension of their subsidy policies, as by obtaining public funding the non-treated firms would significantly increase both, internal R&D expenditure as well as total innovation intensity (though the former only at the 10% significance level for Flanders).

[Insert Table 5, matching results: treatment on the untreated, about here]

The two matching results, i.e. the treatment on the treated and the treatment on the untreated, can now be combined in order to test for misallocation of public funds. Table 6 presents the estimated treatment effects and the Lechner-corrected standard errors. This information is used to compute a t-test on mean difference. Misallocation of public funds would be found if the treatment effect of the untreated is significantly larger than the treatment effect on the treated. As the results show, the analysis does not uncover any systematic misallocation of public funding in this case. Although some treatment effects on the untreated are larger than the estimated treatment effects on the treated, e.g. in Luxembourg, no difference is significantly different from zero. While this result is reassuring with respect to current policy practice, it appears that more research should be done on possible misallocation. First, our analysis is limited in covariates, and more detailed data would be desirable as more precise matching estimations could be conducted. Second, the insignificance of t-tests in the misallocation exercise also suggests that the governments are not necessarily following a successful picking-the-winner strategy, as the treatment effects on the treated are not significantly larger than the treatment on the untreated. Only for Spain, we find some weak evidence at the 10% level that the treated did actually invest more compared to the situation where other firms would have been funded.

[Insert Table 6, testing for misallocation of public funds, about here]

6. Conclusions

In this paper, we conduct a treatment effects study on harmonized data from five different countries, or six different regions, respectively, as Eastern and Western Germany are analyzed separately. In line with recent literature on the effects of public R&D or innovation subsidies, we find that full crowding out effects can be rejected. A novel feature of this study is that the data allow concluding that possible heterogeneity in results stem from actual differences in the policy use across different economies, as the data sources are based on largely harmonized innovation surveys from different countries.

A further attribute of the study is the analysis of the treatment effect on the untreated, where we find evidence that untreated firms would actually have benefitted from receiving subsidies. Indeed, we estimate that such firms would have invested significantly more in case of a treatment.

Finally, we also introduce calculations of possible misallocation of public innovation subsidies to this strand of literature. However, with the data at hand, we do neither find a misallocation nor a superiority of the actual policy decision, as the actual treated firms do not invest significantly more than the non-treated firms would have invested if they had received a subsidy.

Of course, it has to be noted that our study is not without limitations. Although we benefit from harmonized data from different countries, this comes not without a price when compared to other existing studies. First, our nearest-neighbor matching exercise controls only for selection on observables and uses less covariates than other studies cited in this paper that only used data from one country but had more detailed information on the firms in the sample. Second, we cannot control for fixed firm effects as we have to rely on a single cross-section. The availability of panel data would be desirable. If one could control for fixed effects by using a (conditional) difference-in-difference estimator, for instance, the concern of having only few covariates would certainly be much reduced. Finally, let us note that we attempted to overcome the limitation with respect to selection on observables by applying parametric treatment models that allow controlling for selection on unobservables. However, the available data did not contain a convincing exclusion restriction, i.e. a variable that influences the probability of subsidy receipt, but not the outcome variables. Therefore, we refrained from discussing these results in more detail as the treatment effects identification is poor in these models with the given data. Consequently, we were not able to apply instrumental variable techniques either, which would also offer an approach to deal with selection on unobservables.

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Table 2: Descriptive Statistics

	Flanders (full sample N=805)					Western Germany (full sample N=1491)					Eastern Germany (full sample N=730)				
	Non-subsidized firms N=568		Subsidized firms N=237		p-value of t-test on mean difference	Non-subsidized firms N= 1190		Subsidized firms N= 301		p-value of t-test on mean difference	Non-subsidized firms N= 420		Subsidized firms N= 310		p-value of t-test on mean difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
							Covariates								
LNAGE	3.097	0.858	3.099	0.874	p = 0.974	3.159	0.924	3.030	0.936	p = 0.033	2.573	0.581	2.445	0.422	p < 0.001
LOGEMP2002[1]	3.914	1.389	4.317	1.803	p = 0.002	4.273	1.745	4.900	2.145	p < 0.001	3.554	1.410	3.680	1.365	p = 0.227
FOREIGN	0.310	0.463	0.245	0.431	p = 0.056	0.520	0.500	0.555	0.498	p < 0.282	0.512	0.500	0.535	0.500	p = 0.529
GP	0.563	0.496	0.603	0.490	p = 0.293	0.631	0.483	0.704	0.457	p = 0.015	0.557	0.497	0.610	0.489	p = 0.155
KINT2002[2]	5.074	13.160	8.023	15.952	p < 0.012	0.013	0.027	0.020	0.049	p = 0.010	0.015	0.070	0.018	0.045	p = 0.467
d(kint=missing)	0.637	0.481	0.464	0.500	p < 0.001										
PERM_RD_INT	0.405	0.491	0.726	0.447	p < 0.001	0.324	0.468	0.751	0.433	p < 0.001	0.202	0.402	0.619	0.486	p < 0.001
EXPORT	0.759	0.428	0.916	0.279	p < 0.001	0.539	0.499	0.804	0.398	p < 0.001	0.329	0.470	0.619	0.486	p < 0.001
Propensity score	0.279	0.161	0.408	0.174	p < 0.001	0.166	0.147	0.346	0.172	p < 0.001	0.325	0.213	0.572	0.216	p < 0.001
							Outcome variables								
INNOV_INT	4.047	8.840	12.692	18.633	p < 0.001	4.854	8.565	11.823	14.543	p < 0.001	5.105	9.016	16.380	19.314	p < 0.001
INT_RD_INT	1.872	5.961	8.269	14.503	p < 0.001	1.852	4.686	7.243	10.581	p < 0.001	1.141	3.565	9.831	14.521	p < 0.001

…. Table 2 continued

	Spain (full sample N=6006)					Luxembourg (full sample N=248)					South Africa (full sample N=510)				
	Non-subsidized firms N= 3136		**Subsidized firms N= 2870**		**p-value of t-test on mean difference**	**Non-subsidized firms N= 175**		**Subsidized firms N= 73**		**p-value of t-test on mean difference**	**Non-subsidized firms N= 447**		**Subsidized firms N= 63**		**p-value of t-test on mean difference**
Variable	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Covariates															
LNAGE						2.693	0.932	2.823	1.070	p = 0.366					
LOGEMP2002[1]	4.326	1.515	3.911	1.538	p < 0.001	3.849	1.291	4.634	1.480	p < 0.001	4.543	1.665	5.103	2.106	p = 0.047
FOREIGN	0.765	0.424	0.751	0.433	p = 0.202	0.434	0.497	0.356	0.482	p = 0.251	0.260	0.439	0.175	0.383	p = 0.019
GP	0.402	0.490	0.339	0.474	p < 0.001	0.629	0.485	0.699	0.462	p = 0.285	0.510	0.500	0.444	0.501	p = 0.333
KINT2002[2]	6.771	12.234	7.808	12.432	p < 0.001	5.661	10.836	6.496	7.141	p = 0.476					
PERM_RD_INT	0.578	0.494	0.714	0.452	p < 0.001	0.326	0.470	0.493	0.503	p = 0.016	0.371	0.484	0.540	0.502	p = 0.014
EXPORT	0.676	0.468	0.671	0.470	p = 0.681	0.880	0.326	0.890	0.315	p = 0.814	0.582	0.494	0.587	0.496	p = 0.933
Propensity score	0.444	0.139	0.515	0.115	p < 0.001	0.247	0.152	0.409	0.203	p < 0.001	0.115	0.085	0.182	0.097	p < 0.001
Outcomes variables															
INNOV_INT	3.841	8.566	11.108	17.299	p < 0.001	4.358	10.311	6.614	11.330	p = 0.145	4.358	9.830	9.852	16.453	p = 0.012
INT_RD_INT	2.873	7.356	8.972	15.299	p < 0.001	1.729	6.431	3.907	10.997	p = 0.117	1.080	3.141	3.085	7.355	p = 0.036

[1]For Spain data of 2003 is used; for South Africa data of 2004 is used.

[2]For Germany (Western and Easter) and Spain data of 2003 is used.

Table 3: Probit regressions on subsidy receipt

	Flanders	Western Germany	Eastern Germany	Spain	Luxembourg	South Africa
	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)
LNAGE	-0.089	-0.117*	-0.124		-0.103	
	(0.066)	(0.048)	(0.110)		(0.103)	
LOGEMP2002[1]	0.080	0.062*	-0.040	-0.072***	0.245**	0.095
	(0.042)	(0.027)	(0.045)	0.013	(0.080)	(0.049)
FOREIGN	-0.368**	0.073	0.143	-0.387***	-0.465	-0.283
	(0.138)	(0.126)	(0.230)	0.060	(0.261)	(0.232)
GP	-0.004	-0.118	0.009	-0.294***	0.277	-0.196
	(0.127)	(0.145)	(0.239)	0.058	(0.251)	(0.194)
KINT2002[2]	0.004	5.349***	0.990	0.007***	0.003	
	(0.004)	(1.293)	(0.816)	0.001	(0.010)	
d(kint=missing)	-0.251*					
	(0.121)					
PERM_RD_INT	0.588***	0.756***	0.852***	0.331***	0.222	0.419*
	(0.113)	(0.091)	(0.118)	0.036	(0.201)	(0.164)
EXPORT	0.605***	0.369***	0.263*	0.007	-0.225	0.004
	(0.156)	(0.103)	(0.121)	0.040	(0.303)	(0.165)
Constant term	-1.342***	-1.824***	-0.272	0.444***	-0.592	-1.423**
	(0.342)	(0.350)	(0.427)	0.097	(0.517)	(0.445)
Test on joint significance on industry dummies	$\chi^2(12)=20.94$*	$\chi^2(12)=38.19$***	$\chi^2(12)=38.44$***	$\chi^2(12)=148.34$***	$\chi^2(10)=15.39$	$\chi^2(11)=19.04$*
LR test on model significance	$\chi^2(20)=135.5$***	$\chi^2(19)=266.3$***	$\chi^2(19)=192.1$***	$\chi^2(18)=456.7$***	$\chi^2(17)=40.8$***	$\chi^2(16)=34.4$**
McFadden R^2	0.139	0.177	0.196	0.055	0.136	0.0901
# of obs.	805	1491	715	6006	248	510

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

[1]For Spain data of 2003 is used; for South Africa data of 2004 is used.

[2]For Germany (Western and Easter) and Spain data of 2003 is used.

Table 4: Matching results: treatment on the treated

	Flanders (full sample N=805)					Westerns Germany (full sample N=1491)					Eastern Germany (full sample N=730)				
	Selected control group N=235		Subsidized firms N=235[3]		p-value of t-test on mean difference[4]	Selected control group N= 299		Subsidized firms N= 299[3]		p-value of t-test on mean difference[4]	Selected control group N= 310		Subsidized firms N= 310		p-value of t-test on mean difference[4]
Variable	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Covariates															
LNAGE	3.178	0.876	3.101	0.878	p = 0.513	3.028	0.923	3.026	0.937	p = 0.986	2.439	0.516	2.445	0.422	p = 0.931
LOGEMP2002[1]	4.471	1.450	4.311	1.810	p = 0.437	4.698	1.847	4.914	2.144	p = 0.251	3.742	1.423	3.679	1.365	p = 0.736
FOREIGN	0.247	0.432	0.247	0.432	p = 1.000	0.592	0.492	0.558	0.497	p = 0.480	0.593	0.492	0.535	0.499	p = 0.375
GP	0.610	0.489	0.600	0.491	p = 0.896	0.742	0.438	0.710	0.455	p = 0.432	0.677	0.468	0.610	0.488	p = 0.279
d(kint=missing)	0.494	0.501	0.468	0.500	p = 0.703										
KINT2002[2]	4.890	11.632	7.736	15.230	p = 0.091	0.015	0.035	0.017	0.033	p = 0.614	0.012	0.016	0.017	0.045	p = 0.078
PERM_RD_INT	0.720	0.450	0.723	0.448	p = 0.944	0.742	0.438	0.749	0.434	p = 0.873	0.632	0.483	0.619	0.486	p = 0.841
EXPORT	0.911	0.286	0.915	0.279	p = 0.911	0.793	0.406	0.803	0.399	p = 0.795	0.535	0.499	0.619	0.486	p = 0.203
Propensity score	0.401	0.169	0.405	0.171	p = 0.852	0.339	0.161	0.342	0.164	p = 0.830	0.572	0.215	0.572	0.216	p = 0.992
Outcome variables															
INNOV_INT	5,845	10.839	12.477	18.285	p < 0.001	6.699	8.183	11.845	14.578	p < 0.001	7.663	10.925	16.380	19.313	p < 0.001
INT_RD_INT	2,959	6.042	8.026	13.970	p < 0.001	3.549	5.578	7.240	10.599	p < 0.001	2.425	4.235	9.831	14.520	p < 0.001

[1]For Spain data of 2003 is used; for South Africa data of 2004 is used.

[2]For Germany (Western and Easter) and Spain, data of 2003 is used.

[3]Two observations were lost because no common support could be found.

[4]t-statistics are based on Lechner's (2001) asymptotic approximation of the standard errors that accounts for sampling with replacement in the selected control group.

...Table 4 continued

	Spain (full sample N=6006)					Luxembourg (full sample N=248)					South Africa (full sample N=510)				
	Selected control group N=2869		**Subsidized firms N= 2869[5]**		**p-value of t-test on mean difference[4]**	**Selected control group N= 70[6]**		**Subsidized firms N= 70**		**p-value of t-test on mean difference[4]**	**Selected control group N= 63**		**Subsidized firms N= 63**		**p-value of t-test on mean difference[4]**
Variable	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Covariates															
LNAGE						2.815	0.873	2.846	1.022	p = 0.864					
LOGEMP2002[1]	3.907	1.428	3.911	1.537	p = 0.933	4.412	1.358	4.537	1.414	p = 0.645	5.251	2.315	5.103	2.106	p = 0.730
FOREIGN	0.763	0.425	0.750	0.433	p = 0.401	0.357	0.483	0.371	0.487	p = 0.881	0.222	0.419	0.175	0.383	p = 0.539
GP	0.323	0.467	0.339	0.473	p = 0.334	0.643	0.483	0.686	0.468	p = 0.648	0.460	0.502	0.444	0.500	p = 0.869
KINT2002[2]	7.779	14.158	7.785	12.377	p = 0.990	6.478	7.453	6.280	7.039	p = 0.891					
PERM_RD_INT	0.713	0.452	0.713	0.452	p = 1.000	0.543	0.502	0.486	0.503	p = 0.564	0.651	0.481	0.540	0.502	p = 0.237
EXPORT	0.667	0.471	0.671	0.469	p = 0.810	0.857	0.352	0.886	0.320	p = 0.670	0.666	0.475	0.587	0.496	p = 0.393
Propensity score	0.515	0.115	0.515	0.115	p = 0.999	0.390	0.185	0.391	0.186	p = 0.978	0.182	0.097	0.182	0.097	p = 1.000
Outcome variables															
INNOV_INT	5.808	11.198	11.108	17.302	p < 0.001	3.369	3.655	6.696	11.543	p = 0.026	4.172	6.533	9.852	16.453	p = 0.012
INT_RD_INT	4.888	10.304	8.971	15.302	p < 0.001	1.197	2.018	3.931	11.221	p = 0.047	1.491	3.525	3.085	7.355	p = 0.132

[4]t-statistics are based on Lechner's (2001) asymptotic approximation of the standard errors that accounts for sampling with replacement in the selected control group.

[5]One observation was lost because no common support was found.

[6]Three observations were lost because no common support was found.

Table 5: Matching results: treatment on the untreated

	Flanders (full sample N=805)					Westerns Germany (full sample N=1491)					Eastern Germany (full sample N=730)				
	Selected control group N=545		**Non-subsidized firms N=545[3]**		**p-value of t-test on mean difference[5]**	**Selected control group N= 1168**		**Non-subsidized firms N= 1168[4]**		**p-value of t-test on mean difference[5]**	**Selected control group N= 391[7]**		**Non-subsidized firms N= 391**		**p-value of t-test on mean difference[5]**
Variable	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
							Covariates								
LNAGE	3.063	0.839	3.103	0.853	p = 0.713	3.143	0.910	3.146	0.922	p = 0.985	2.547	0.418	2.549	0.552	p = 0.968
LOGEMP2002[1]	4.062	1.565	3.936	1.390	p = 0.532	4.176	1.758	4.298	1.746	p = 0.569	3.640	1.325	3.569	1.344	p = 0.694
FOREIGN	0.301	0.459	0.301	0.459	p = 1.000	0.488	0.500	0.520	0.500	p = 0.603	0.522	0.500	0.512	0.501	p = 0.879
GP	0.554	0.498	0.561	0.497	p = 0.909	0.652	0.476	0.633	0.482	p = 0.734	0.591	0.492	0.558	0.497	p = 0.617
KINT2002[2]	4.097	9.843	5.288	13.393	p = 0.372	0.015	0.025	0.013	0.027	p = 0.496	0.018	0.026	0.015	0.072	p = 0.630
d(kint=missing)	0.640	0.480	0.622	0.485	p = 0.768										
PERM_RD_INT	0.428	0.495	0.422	0.494	p = 0.932	0.322	0.467	0.330	0.471	p = 0.880	0.217	0.413	0.212	0.409	p = 0.927
EXPORT	0.789	0.408	0.791	0.407	p = 0.972	0.634	0.482	0.549	0.498	p = 0.145	0.399	0.490	0.345	0.476	p = 0.414
Propensity score	0.738	0.154	0.742	0.158	p = 0.822	0.828	0.144	0.831	0.147	p = 0.863	0.666	0.207	0.667	0.207	p = 0.992
							Outcome variables								
INNOV_INT	8.449	14.695	4.153	8.959	p = 0.019	9.275	12.990	4.888	8.617	p = 0.005	11.463	15.515	5.271	9.262	p = 0.002
INT_RD_INT	4.042	9.980	1.908	6.014	p = 0.087	3.965	7.389	1.884	4.724	p = 0.019	5.847	11.948	1.187	3.670	p = 0.002

[1]For Spain data of 2003 is used; for South Africa data of 2004 is used.

[2]For Germany (Western and Easter) and Spain, data of 2003 is used.

[3]Twenty-three observations were lost because of no common support.

[4]Twenty-two observations were lost because no common support could be found.

[5]t-statistics are based on Lechner's (2001) asymptotic approximation of the standard errors that accounts for sampling with replacement in the selected control group.

… Table 5 continued

	Spain (full sample N=6006)					Luxembourg (full sample N=248)					South Africa (full sample N=510)				
	Selected control group N=3112		**Non-subsidized firms N=3112[6]**		**p-value of t-test on mean difference[5]**	**Selected control group N= 165[8]**		**Non-subsidized firms N= 165**		**p-value of t-test on mean difference[5]**	**Selected control group N= 409[9]**		**Non-subsidized firms N= 409**		**p-value of t-test on mean difference[5]**
Variable	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
							Covariates								
LNAGE						2,550	0,837	2,687	0,946	p = 0,432					
LOGEMP2002[1]	4.386	1.650	4.308	1.502	p = 0.199	3.670	1.369	3.950	1.248	p = 0.309	4.832	1.987	4.605	1.665	p = 0.588
FOREIGN	0.772	0.420	0.764	0.425	p = 0.625	0.467	0.500	0.424	0.496	p = 0.667	0.218	0.413	0.240	0.427	p = 0.803
GP	0.395	0.489	0.399	0.489	p = 0.847	0.630	0.484	0.630	0.484	p = 1.000	0.460	0.499	0.504	0.501	p = 0.679
KINT2002[2]	6.994	11.470	6.790	12.266	p = 0.641	5.346	6.475	5.717	10.817	p = 0.802					
PERM_RD_INT	0.597	0.490	0.583	0.493	p = 0.412	0.442	0.498	0.339	0.475	p = 0.307	0.411	0.493	0.391	0.489	p = 0.852
EXPORT	0.683	0.466	0.679	0.467	p = 0.840	0.885	0.320	0.873	0.334	p = 0.854	0.528	0.500	0.575	0.495	p = 0.662
Propensity score	0.553	0.135	0.553	0.135	p = 0.998	0.741	0.149	0.741	0.149	p = 0.998	0.879	0.078	0.879	0.078	p = 0.984
							Outcome variables								
INNOV_INT	7.855	14.548	3.868	8.593	$p < 0.001$	13.821	23.640	4.527	10.582	p = 0.040	9.993	16.733	4.459	10.216	p = 0.123
INT_RD_INT	6.053	12.640	2.895	7.380	$p < 0.001$	11.570	24.232	1.808	6.610	p = 0.034	4.416	10.014	1.158	3.267	p = 0.117

[5]t-statistics are based on Lechner's (2001) asymptotic approximation of the standard errors that accounts for sampling with replacement in the selected control group.

[6]Twenty-four observations were lost because no common support was found.

[7]Twenty-nine observations were lost because of no common support.

[8]Ten observations were lost because no common support was found.

[9]Thirty-eight observations were lost because no common support was found.

Table 6: t-tests on misallocation of public funding

	Flanders (full sample N=805)					Westerns Germany (full sample N=1491)					Eastern Germany (full sample N=730)				
	Estimated treatment effect on the treated		**Estimated treatment effect on the untreated**		**p-value of t-test on mean difference**	**Estimated treatment effect on the treated**		**Estimated treatment effect on the untreated**		**p-value of t-test on mean difference**	**Estimated treatment effect on the treated**		**Estimated treatment effect on the untreated**		**p-value of t-test on mean difference**
	N=235		**N=545**			**N=229**		**N=1168**			**N=310**		**N=391**		
Variable	Alpha	Std. err.	Alpha	Std. err.		Alpha	Std. err.	Alpha	Std. err.		Alpha	Std. err.	Alpha	Std. err.	
INNOV_INT	6.631	1,738	4.296	1.837	p = 0.4399	5.145	1.050	4.387	1.556	p = 0.8307	8.717	1.708	6.193	1.993	p = 0.3513
INT_RD_INT	5.066	1,152	2.133	1.247	p = 0.1518	3.690	0.747	2.081	0.884	p = 0.4268	7.405	0.968	4.661	1.503	p = 0.1482
	Spain (full sample N=6006)					**Luxembourg (full sample N=248)**					**South Africa (full sample N=510)**				
	N= 2869		**N= 3112**			**N= 70**		**N= 165**			**N= 63**		**N= 409**		
Variable	Alpha	Std. err.	Alpha	Std. err.		Alpha	Std. err.	Alpha	Std. err.		Alpha	Std. err.	Alpha	Std. err.	
INNOV_INT	5.300	0.481	3.986	0.504	p = 0.0602	3.328	1.494	9.293	4.531	p = 0.3972	5.681	2.278	5.394	3.499	p = 0.9745
INT_RD_INT	4.091	0.435	3.157	0.437	p = 0.1306	2.733	1.378	9.762	4.596	p = 0.3247	1.594	1.058	3.358	2.079	p = 0.7545

Table A.7: OLS estimates on internal R&D intensity

	Flanders	Western Germany	Eastern Germany	Spain	Luxembourg	South Africa
	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)
SUBSIDY DUMMY	4.066***	3.326***	5.711***	3.799***	3.062*	1.895*
	(0.730)	(0.543)	(0.682)	(0.250)	(1.700)	(0.960)
LNAGE	-0.482	-0.576***	-0.262		-0.443	-0.395*
	(0.363)	(0.151)	(0.535)		(0.466)	(0.159)
LOGEMP2002[1]	-0.730**	-0.670***	-1.068***	-2.023***	-1.293	
	(0.256)	(0.101)	(0.231)	(0.120)	(0.732)	
FOREIGN	0.628	0.451	-1.193	0.592	2.222	0.065
	(0.809)	(0.456)	(1.858)	(0.317)	(1.793)	(0.403)
GP	-0.507	-0.895	0.494	0.500	-0.966	-0.051
	(0.816)	(0.539)	(1.905)	(0.326)	(0.949)	(0.385)
KINT2002[2]	0.061	-2.724	-2.811	0.046***	-0.028	
	(0.037)	(4.063)	(2.469)	(0.012)	(0.036)	
d(kint=missing)	0.768					
	(0.709)					
PERM_RD_INT	4.934***	3.532***	3.769***	3.996***	5.619***	1.331***
	(0.669)	(0.373)	(0.802)	(0.256)	(1.616)	(0.354)
EXPORT	1.262	0.727*	2.126*	-0.896*	1.473	-0.006
	(0.772)	(0.346)	(0.853)	(0.376)	(1.682)	(0.323)
Constant term	1.482	4.343***	2.198	6.373***	3.783	2.317*
	(1.887)	(0.790)	(1.782)	(0.668)	(2.352)	(0.942)
Test on joint significance on industry dummies	F(12. 783) = 6.51***	F(12. 1470)=9.72***	F(13. 708) = 4.84***	F(12. 5986) = 36.73***	F(10.229) = 1.09	F(11. 492) = 1.32
F-test	F(21. 783) = 8.45***	F(20. 1470)=15.85***	F(21. 708)=10.41***	F(19. 5986)=64.18***	F(18. 229) = 2.50***	F(17.492)=3.23***
R-squared	0.345	0.313	0.350	0.311	0.217	0.105
# of obs.	805	1491	730	6006	248	510

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

[1]For Spain data of 2003 is used; for South Africa data of 2004 is used.

[2]For Germany (Western and Easter) and Spain data of 2003 is used.

Table A.8: OLS estimates on total innovation intenstity

	Flanders	Western Germany	Eastern Germany	Spain	Luxembourg	South Africa
	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)
SUBSIDY DUMMY	6.245***	4.899***	8.052***	4.692***	3.226*	4.712*
	(1.174)	(0.808)	(1.142)	(0.288)	(1.802)	(2.101)
LNAGE	-0.652	-0.680*	-1.426		-0.892	
	(0.552)	(0.268)	(0.793)		(0.747)	
LOGEMP2002[1]	-1.054**	-1.522***	-1.755***	-2.499***	-1.451	-0.425
	(0.352)	(0.174)	(0.361)	(0.137)	(0.768)	(0.454)
FOREIGN	1.187	0.584	0.592	0.766*	1.141	1.121
	(0.946)	(0.615)	(2.242)	(0.382)	(2.082)	(0.860)
GP	-2.625*	-1.123	-0.364	0.953*	-0.247	-3.378**
	(1.036)	(0.756)	(2.303)	(0.390)	(1.877)	(1.189)
KINT2002[2]	0.063	13.513	1.593	0.081***	-0.035	
	(0.043)	(10.642)	(6.790)	(0.013)	(0.054)	
d(kint=missing)	0.023					
	(0.983)					
PERM_RD_INT	5.343***	3.915***	3.805**	3.708***	4.799**	0.927
	(1.007)	(0.587)	(1.207)	(0.298)	(1.807)	(1.039)
EXPORT	0.201	0.927	2.040	-1.165**	1.950	0.133
	(1.224)	(0.618)	(1.327)	(0.431)	(2.401)	(1.001)
Constant term	7.565*	9.942***	11.118***	8.948***	7.408*	8.447*
	(2.965)	(1.406)	(2.900)	(0.786)	(2.919)	(3.414)
Test on joint significance on industry dummies	F(12. 783) = 5.74***	F(12. 1470)=8.33***	F(13. 708) = 4.41***	F(12. 5986) = 34.58***	F(10.229) = 0.97	F(11. 492) = 2.78**
F-test	F(21. 783) = 7.94***	F(20. 1470)=13.69***	F(21. 708)=10.46***	F(19. 5986)=63.75***	F(18. 229) = 2.44**	F(17.492)=3.13***
R-squared	0.255	0.249	0.287	0.309	0.158	0.120
# of obs.	805	1491	730	6006	248	510

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

[1]For Spain data of 2003 is used; for South Africa data of 2004 is used.

[2]For Germany (Western and Eastern) and Spain data of 2003 is used.