Value for money? New microeconometric evidence on the input additionality of R&D grants in Flanders[*]

Dirk Czarnitzki [a, b, c] and Cindy Lopes Bento [a, c, d]

a)K.U.Leuven, Dept. of Managerial Economics, Strategy and Innovation, Leuven
b) Centre for R&D Monitoring (ECOOM) at K.U.Leuven
c) Centre for European Economic Research (ZEW), Mannheim
d) CEPS/INSTEAD, Luxembourg

November 2011

Abstract

A significant amount of money is spent on programs to stimulate innovative activities. In this analysis, we review the effects of a specific government-sponsored commercial R&D program from various angles. We start by evaluating whether we find positive effects of subsidies on R&D investment and (R&D) employment. Then, we analyze how the observed effects of subsidies on R&D intensity and employment vary over time, vary depending on how many supported projects a single firm has at the same time or vary if a same firm gets support consecutively. Finally, we estimate the macroeconomic impact these grants have on the local economy in terms of (R&D) employment. We conclude that the policies do not create crowding out effects or weaker effects over time, by project or for "consecutive clients" and find that, on average, five jobs are created per supported project.

[*] Financial support from the IWT (agency for Innovation by Science and Technology) as well as of the Fonds National de la Recherche Luxembourg (FNR) is greatfully acknoledged.

1. Introduction

The impact of subsidies on firms' innovative behaviour has been of interest in economic literature for many years now. In line with this literature, we are interested in knowing what the effect of one specific type of subsidy is on firms' R&D intensity and employment behavior, namely the effect of local subsidies for R&D from the Flemish government (northern part of Belgium). The goal is to analyse whether firms that get local subsidies invest more in R&D and R&D employment than firms that do not get local public support. Furthermore, we want to know whether firms that receive grants for several projects at the same time, respectively for several years in a row have different effects over time and per project from firms that receive support only punctually.

While many papers in economic literature investigated the impact of subsidies at the firm level, these studies generally consider subsidies stemming from different sources as support to R&D, without differentiating between the origin of the funds. As a matter of fact, public funding schemes are available on many different levels (i.e. regional, national, European), each one of which pursuing different goals and following different selection criteria. As a consequence, even though these studies offer a good analysis on the general impact of direct support on R&D, the focus of one specific program is often lacking in empirical literature, rendering the evaluation of one particular program very difficult. Even though some more recent studies take into account the fact that the impact of a subsidy might change depending on whether it stems from a national or an international funding agency (see e.g. Garcia and Mohnen, 2010 or Czarnitzki and Lopes Bento, 2011), the focus of one specific national or local program is often lacking.

A further issue that is often not taken into account in existing empirical literature is the duration of a project for which a single grant is distributed to a firm or the information on how many projects a single firm got subsidies for at the same time. If a subsidized project is running over several years or if one firm receives subsidies recurrently, one question that arises is to know whether the additionality effects that one might observe in period one will remain stable (or decline) in subsequent periods. This is indeed useful information for a funding agency, in that it will allow it to conclude whether "recurrent clients" should be privileged because of their experience or whether the gain would be higher if "new clients" were chosen more frequently. This paper intends to contribute to the literature by taking these aspects into account and by evaluating the effect that local subsidies have on a representative sample of northern Belgium firms with regards to R&D intensity and employment in general, in the case of multiple simultaneously supported projects and for recurrently financed firms.

Finally, we estimate the impact that Flemish subsidies have on the local economy. More precisely, through a back-of-the-envelope estimation, we assess how many R&D jobs are created (or secured) because of the receipt of a subsidy, and what share of these costs are covered by public respectively private funds.

The following section will provide an overview on the institutional background and functioning of the funding agency. Section three reviews the existing literature and the undermining theory. In section 4, we present the econometric method. Section 5 provides information on the data. Section 6 displays the econometric results and section 7 provides information on the macroeconomic effect of the Flemish innovation policy on the Flemish economy. Section 8 concludes.

2. Institutional background[2]

The IWT

The agency for Innovation by Science and Technology in Flanders / agentschap voor Innovatie door Wetenschap en Technologie in Vlaanderen (IWT) is a governmental agency, established by the Flemish Government in 1991. It was established to give shape to the new competences in science and technology that were transferred from the federal to the regional governments in Belgium. Since this transfer of competences made of innovation policies a regional matter, the IWT has been created as the key organization for support and promotion of R&D and innovation in Flanders. Indeed, at a regional level, the IWT is the only entity awarding grants to Flemish firms. In addition to offering Flemish companies and research centres financial support, advice and a network of potential partners in Flanders and abroad, it also supports the Flemish Government in defining and adapting its innovation policy.

The total funding of the IWT amounted to € 297 million in 2008. The scope of existing funding programs is quite broad, including industrial R&D projects, EUREKA-projects, feasibility studies and innovation projects for SME's, support to industrial networks (sectoral research, technological advisory services, innovation stimulation), support to universities for strategic basic research (SBO), support to higher education engineering schools for technology diffusion actions (HOBU/TETRA), individual grants for PhD and post-doc research, support to universities for exploitation of their R&D-results and to larger "ad hoc " initiatives as decided by the Flemish government. As a matter of illustration, in 2008, about 341 industrial projects (R&D

[2] The background information and stylized facts stem from Larosse (2011), http://www.eurotransbio.eu and www.iwt.be.

business projects and SME program) were funded for a total amount of € 110,042 million of which approximately 30% is in the larger Biotech area.

The mission of all Flemish R&D and innovation initiatives, is to create a region of excellence by performing both basic as well as applied research activities. This region of excellence pursues the goal to establish a sound basis through fundamental research activities and to create a dynamic environment for translating the basic understanding in R&D efforts that strengthen the economic fabric.

In its competence of also coordinating regional innovation initiatives such as regional development agencies, technological advisory services, sectoral research centres and industrial federations, the IWT can be viewed as both, a program owner (in close co-operation with the Flemish Minister of Innovation) and a program manager (selection and follow-up of research and innovation projects).

Funding by the IWT

The IWT has a yearly budget of around € 300 million to financially support R&D and innovation in Flemish firms. These funds are directed to small as well as large companies, universities, third level education institutions and other Flemish innovative players, individually or collectively. A wide range of activities is supported through this financial support, including feasibility studies, research and development projects for companies, strategic basic research and grants for research institutions and researchers, network projects and translation research for intermediary organizations.

Every year, some 600 companies benefit from IWT support (overall support, all measures cumulated). While in the past it was mainly manufacturing companies that have solicited the support of the IWT, nowadays, service providers are more and more represented.

In order to encourage smaller firms to perform R&D, a special program for SMEs has been put in place (the “KMO programma”). The maximum project costs a firm can submit under this program is of € 200,000. Of these total project costs, the maximum subsidy rate is of 35% for a medium-sized company, and an extra 10% (hence 45% of the total project costs) for a small-sized company. If an SME collaborates with a public research institute or an international partner, it can submit a proposal of a maximum of € 250,000. If it collaborates with another firm (nationally), it can get 10% top-up in the subsidy rate.

Besides the KMO program, the IWT has the R&D program. In the latter, the basic subsidy rate that is of 15% for development and 40% for research. Furthermore, additional 10% are available for medium-sized enterprises and 20% additional support for small firms. Further support may be granted to projects that meet specific policy targets, like e.g. the promotion of sustainable technological development or cooperation with research institution. Finally, an extra 10% of support may be granted to projects involving substantial collaboration of several companies, provided that at least one is an SME or that the project entails an international cooperation. The general feature of the IWT subsidy scheme is its bottom-up character: it is a permanently open and non-thematic scheme.

With regards to the evaluation procedures, the IWT has a well-developed set of procedures for project evaluation, based on internal and external referees to evaluate the ex-ante effectiveness of the project proposals (ex-post evaluation is starting up).

Initially, the evaluation criteria were heavily focussed on the scientific qualities and technological risks of the project. Gradually however, the economic dimension became equally - or even more - important, reflecting the shift from a purely R&D policy towards a more innovation related policy focus. This economic evaluation doesn't only concern the financial feasibility of the project or the commercial prospects for the innovating firm but also the economic return 'for Flanders'. The most important economic criterion is that the project must be able to generate an economic value added that is at least ten times the value of the subsidy.

As part of the IWT's evaluation, the 'societal' qualities of the project – mainly concerning environmental sustainable development – are also considered, though to a much lesser extent than the economic criteria. However, because of the formal policy objective to increase the number of projects that support sustainable development, the latter criteria were formally separated from the standard project evaluation. Hence, this arrangement applies across the existing subsidy schemes and implies an additional evaluation of candidate projects on criteria of 'eco-efficiency'. The evaluation gives access to extra support in the form of a priority ranking across existing subsidy schemes and of a financial bonus of 10% on the project budget. Hence, project evaluation in Flanders is closely linked to general policy criteria in a bottom-up innovation policy design.

3. Theoretical premises and literature review of R&D subsidy policies

3.1. Theory

In economic literature, the impact of innovation policies - and particularly direct subsidies for R&D - on firms' innovative behaviour has been of interest for many years now. The economic justification for governmental intervention for private sector R&D activities relies on the familiar market failure arguments (Arrow, 1962). Given these market failure arguments, most governments in industrialized economies intervene in order to correct them to the best possible extent by designing specific policies, like for instance Intellectual Property Rights to improve appropriability of knowledge (see e.g. Hall, 2002 for a survey), tax reliefs to reduce the cost of R&D (see Hall and Van Reenen, 2000) or low interest rates. A detailed overview of the existing policy mix and its potential effects on R&D activities would however be beyond the scope of this study, since we are merely interested in direct subsidies.

According to Arrow (1962), the market failure arguments can be summarized into three main issues: (i) increasing returns, (ii) inappropriability of knowledge and (iii) uncertainty.

(i) Information is characterized by increasing returns to scale insofar that once the information is produced, it can be used multiple times, regardless of the scale of production. Since the same unit of information can be used multiple times by the same or by a different user, the cost of information production is not dependent on the scale on which the information is used (Arrow, 1962, 1996, 1999; Lamberton, 1996). There are generally relative high fixed costs of establishing an economic unit for the production of information and the marginal cost of providing a unit of information is far less than the average costs of information production. Indeed, from a welfare point of view, the information concerning an invention should be available completely free of charge, with the exception of the cost of transmitting the information (often very low or close to zero though). Even though this would ensure an optimal utilization of the information, it would present very little, if not no, incentive to invest in knowledge production.

(ii) In terms of inappropriability, it is a well-known fact that because of the non-rival and non-exclusive character of knowledge, a firm can never appropriate all the benefits of its R&D investments, even though it has to bear the entire costs. A part of the created knowledge always spills over to other agents, so that many agents can benefit from an investment done by the one firm. Hence, the incentive to be the investing agent is reduced due to this inappropriability of knowledge.

(iii) The third argument is linked to the uncertainty that is concurrent to innovative activities. As a matter of fact, innovation is not only uncertain in that one does not always know whether the desired result of the technological change or the innovation will be obtained in terms of output, but very often, one cannot be sure about the market success of an innovation either. Indeed, the path from a brilliant idea to a technical invention to a successful market application is long, risky and sinuous. In other words, the output of an invention or an innovation can never be perfectly predicted by its input (Arrow, 1962). Hence, in order to undertake such an uncertain project, a firm has to be willing to bear the inherent risk of this endeavour. Since the assumption is that firms are often risk-averse, this will lead to a sub-optimal allocation of risk, meaning that there will be discrimination against risky projects (Arrow and Lind, 1970). In line with the uncertainty (moral hazard) argument, firms often face financial constraints if they do not have sufficient internal resources to undertake an R&D project. Indeed, R&D investments are generally characterized by high firm specific investment and adjustment costs on the one hand, and low collateral value on the other hand. An important share of R&D investment consists in financing R&D employees and training, and hence, a large part of the investment is immediately sunk. Compared to investment in physical capital, R&D itself cannot be used as collateral in credit negotiations (see Hall (2002) for a comprehensive survey of financial constraints). Hence, R&D investments are often hampered by a lack of external lenders or investors. Finally, the market uncertainty for new products delays investment in R&D, reducing the total R&D in the economy. This is even more accurate for projects of more basic research, as the latter are further away from the market and its potential use may be largely unknown by the time of the investment (see e.g. Czarnitzki and Hottenrott, 2011). Recent literature (real options theory) emphasizes the irreversibility of investments. In other words, firms incur additional opportunity costs by turning down the option to wait for information, and thus by investing today, they eliminate their chance of investing at any time in the future. As a consequence of this uncertainty, investment will decrease (Pindyck and Dixit, 1994).

While the third argument relates to uncertainty and financial market constraints, the two prior arguments, namely the inappropriability of R&D and the increasing returns are associated with positive spillovers and increased consumer surplus. In practice this means that it is socially desirable to subsidize an R&D project if it is associated to high social returns (and provided that the project in question would not have taken place if the firm would have been left on its own). As a consequence of the above, it is a largely shared view that R&D activities are difficult to finance in a freely competitive market place. Support of this view in the form of economic-theory modelling dates back to Schumpeter (1942) and was built upon by Nelson (1959) and Arrow (1962).

3.2.Empirical evidence

The predominant question analyzed by empirical literature is whether public subsidies crowd-out private investment or whether they stimulate them. In a survey of the literature on the impact of public R&D subsidies on private R&D expenditure, David et al. (2000) find that most studies are subject to a potential selection bias. Indeed, since neither the fact of applying, nor the fact of receiving a public subsidy can be viewed as random, the selection into such a process has to be taken into account for the results of an analysis to be correct.

Hall (2005) concludes that in empirical literature since 2000, correctly addressing this selection bias issue, total crowding out effects were only found for the US Small Business Innovation Research (SBIR) program. In the case of this study, the author, basing himself on a sample of 479 observations and using a 3SLS approach, could however not exclude the possibility that the grants might have had a positive effect on keeping the funded firms' R&D activities constant, which might not have been possible otherwise.

Most of the other studies, largely based on cross-sectional data taken from national surveys and often complemented by patent statistics, find positive results for R&D intensity or patent activity.

Other studies in this area include Almus and Czarnitzki (2003) finding that Eastern German firms which received public subsidies increased their innovation activities by about four percentage points; Czarnitzki and Hussinger (2004), finding a positive impact in evaluating the effect of public R&D funding on R&D intensity and patent outcome in Germany; Duguet (2004), focusing on growth of the ratio of firms' R&D to sales for France; Aerts and Czarnitzki (2004) focusing on patent outcome for Flanders, Czarnitzki and Lopes Bento (2011a) in a cross-country comparative evaluation and Czarnitzki and Lopes Bento (2011b) in a multiple treatment effect analysis for German firms, all exclude total crowding out, even though some find evidence of partial crowding out. Takalo et al. (2011) model the application and R&D investment decisions of the firm and the subsidy granting decision of the public agency in charge of the program to estimate the expected welfare effects of targeted R&D subsidies using R&D project level data from Finland. They find that the social rate of return on targeted subsidies is 30-50%, but that spillover effects of subsidies are smaller than effects on firm profits. Gonzalez et al. (2005) use IV models to evaluate R&D policy programs on about 2000 Spanish firms. The authors find that private R&D investment is stimulated by subsidies in Spain. As Gonzales, Busom (2000), applying a parametric selection model, finds that public R&D subsidies stimulate private R&D spending positively on average.

4. Econometric Method

In economics and other social sciences, many empirical questions depend on the causal effects of programs or policies. The central question this literature is interested in is the evaluation of the effect of the exposure of a set of units to a program or a treatment, on some outcome.

Units that participate in a given program or get a certain treatment may however differ from units that are not exposed to this treatment in important characteristics. These differences may invalidate causal comparisons of outcomes by treatment status. Hence, when evaluating such treatment effects, we face a potential selection bias problem which has to be addressed adequately in order for the results to be correct. Modern econometric techniques tackling this issue have been studied for many years now and offer different 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 three cross-sections and not of a panel (73% of the firms are observed only once), we cannot apply this estimator.

For the application of an IV estimator or a selection model, one needs a valid instrument (or an "exclusion restriction" in the selection model case) for the treatment variables. As described in the previous section, special rules exist for SMEs. Besides the fact that SMEs are eligible for a specific program (the KMO program), they receive a higher percentage rate of the total project costs covered depending on whether they are medium-sized enterprises (a maximum of 35% is covered) or small-sized enterprises (a maximum of 45% is covered)[3] provided that they are not part of a group. Hence, a potential instrument for our analysis would have been the inclusion of dummy variables equal to one if a firm qualifies as a small-sized (respectively a medium-sized enterprise) that is not part of a group. As a matter of fact, given the extra expenses covered for small firms in the KMO program, respectively for small and medium sized firms in the R&D program, the eligible firms could have an additional incentive to submit a project to the IWT, given that for the same cost of applying, the potential gain for the latter is higher. Since the definition of small and medium sized is decided upon by the European Commission and since a firm would not choose the number of its employees in light of the eligibility criteria of a specific subsidy program, such a dummy would fulfil the condition of being correlated with the

[3] The definition of medium and small sized firms is the one by the EU, i.e. a firm qualifies as small-sized firm if it has less than 49 employees and less than € 10,000 of turnover. It qulaifies as medium-sized firm if it has between 50 and 249 employees and an annual turnover larger than 10,000 and smaller than € 50,000.

endogenous dummy variable indicating the treatment and uncorrelated with the error term and would hence not have a partial effect on our outcome variables once the we control for the other covariates.

Unfortunately, neither one of these two dummy variable was significant in our selection equation. Since there are no other variables available that would fulfil the necessary conditions to be used as an instrument or an exclusion restriction, the use of control functions are excluded. Hence, the most appropriate choice in our case is the matching estimator. Apart from best fitting our data, this estimator further has the advantage to require fewer functional form and homogeneity assumptions. The downside however is that it only controls for the selection on observables. Hence, we have to maintain the assumption that we observe all important determinants driving the selectivity into program participation, namely the receipt of a local public R&D subsidy. This is a clear limitation when only cross-sectional data are available.

Matching estimators have been applied and discussed by many scholars, amongst which Angrist (1998), Dehejia and Wahba (1999), Heckman et al. (1997, 1998a, 1998b), and Lechner (1999, 2000). Generally, matching estimators are used to answer the question of what treated units with a given set of characteristics would have done if they would not have received the treatment. The objective is to compare the two outcomes – when receiving and when not receiving a treatment – for the same unit. The problem is of course that we can observe at most one of these outcomes because the observed unit has either received a treatment or not. Holland (1986) refers to this as the fundamental problem of causal inference. Hence, the counterfactual situation of a treated firm (i.e. an untreated firm) is not directly observable and has to be estimated.

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. 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. As previously explained, while $E(Y^T|S=1)$ is directly observable, it is not the case for the counterpart. $E(Y^C|S=1)$ has to be estimated. In the case of matching, this potential "untreated outcome" of treated firms is constructed from a control group of firms that did not receive innovation subsidies. The matching relies on the intuitively attractive 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.

Because of a potential selection bias due to the fact that the receipt of a subsidy is not randomly assigned, $E(Y^C|S=1) \neq E(Y^C|S=0)$ and the counterfactual situation cannot simply be estimated as average outcome of the non-participants. Rubin (1977) introduced the conditional independence assumption (CIA) to overcome this selection problem, that is, participation and potential outcome are statistically 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

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

Provided that there no systematic differences in the observed characteristics between both groups, the treatment effect can be written as:

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

In the present analysis, we conduct a variant of the nearest neighbour matching (caliper matching). More precisely, we pair each subsidy recipient with the single closest non-recipient. The pairs are chosen based on the similarity in the estimated probability of receiving such a subsidy, meaning the propensity score stemming from a probit estimation on the dummy indicating the receipt of subsidies *S*. Matching on the propensity score has the advantage not to run into the "curse of dimensionality" since we use only one single index as matching argument (see Rosenbaum and Rubin, 1983). In addition of matching on the propensity score, we also require the observations of firms in the selected control group to belong to the same year and to have a similar patent stock than the firms in the treatment group.

Last but not least, it is essential that there is enough overlap between the control and the treated group. We thus calculate the minimum and the maximum of the propensity scores of the potential control group, and delete observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. In addition to the common support condition, we impose a caliper to the maximum distance we allow between the treated and the control unit. If the distance is above this pre-defined threshold (2 in our case), the observation is dropped from the sample (see Todd and Smith, 2005).

The detail of our matching protocol is summarized in Table 1 and follows Gerfin and Lechner (2002).

Table 1: The matching protocol

Step 1	Specify and estimate a probit model to obtain the propensity score $\hat{P}(X)$.
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. We use caliper matching, first introduced by Cochran and Rubin (1973). The intuition of caliper matching is to avoid “bad” matches (those for which the value of the matching argument Zj is far from Zi) by imposing a threshold of the maximum distance allowed between the treated and the control group. That is, a match for firm i is only chosen if $\lVert Zj - Zi \rVert < \varepsilon$, where ε is a pre-specified tolerance.
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.

5. Data and variables

The data used in this paper stem from the Community Innovation Survey (CIS) of Flanders.[4] More precisely, they stem from the CIS4, covering the years 2002-2004, the CIS5, covering 2004-2006 and CIS6, covering 2006-2008. Furthermore, the data has been complemented by data from the Belfirst dataset and has been merged with information from the ICAROS dataset of the IWT. The latter provides detailed information on the amounts of the grants as well as on grants received in previous periods and the duration of the funded projects.

Our sample concerns innovative as well as non-innovative firms and covers manufacturing as well as business related services sectors.[5] In total, the sample consists of 4,761 observations, out of which 1,948 are innovative firms and 292 received a public R&D subsidy from the Flemish government. Table A1 and A2 in appendix A1 show the industry structure as well as the firm size distribution of our sample.

The receipt of a subsidy form the IWT is denoted by a dummy variable equal to one for firms that received public R&D funding and zero otherwise.

Outcome variables

As outcome variables, we consider the internal R&D investment, *INT_RD_INT*, being the ratio of internal R&D expenditures[6] to sales (multiplied by 100) as well as R&D employment, *RDEMP*, being the ratio of R&D employment to total employment (multiplied by 100).

[4] The CIS covers all of the EU member states, Norway and Iceland using a largely harmonized questionnaire throughout participating countries. The CIS databases contain information on a cross-section of firms active in the manufacturing sector and in selected business services.

[5] According to the 3rd edition of the Oslo Manual – which is the definition followed by the CIS - an innovative firm is one that has 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).

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

Control variables

We use several control variables in our analysis likely to impact the fact of whether or not a firm applies and receives public support for its R&D activities. The number of employees takes into account possible size effects. As the firm size distribution is skewed, the variable enters in logarithms (*LOGEMP*). We also allow for a potential non-linear relationship by including $(LOGEMP)^2$.

In addition, we include a dummy variable capturing whether or not a firm is part of a group (*GP*), and if so, whether it has its headquarters 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. From a governmental point of view, the funding decision might be more positively assessed if a firm is part of a group because of potential incoming knowledge spillovers that can result from foreign branches. On the other hand, firms belonging to a group with a foreign parent company, might be more susceptible to file subsidy applications in their home country. Furthermore, as explained in the previous section, the Flemish government maintains a special policy instruments for small and medium-sized firms, being eligible only if they are not part of a group. If a small firm is majority-owned by a large parent company, it would no longer qualify for the SME-programs. The dummies *GP* and *FOREIGN* thus also control for this type of company profile, and an *a-priori* judgement of whether the effect is positive or negative is complicated because of the two opposing arguments outlined above.

The log of the firm's age (ln*AGE*) is included in the analysis as it is often claimed that older firms are more reluctant to pursue innovation. In addition, the government maintains special policy schemes for start-up companies which make the receipt of funding possibly more likely for younger firms.

Previous experience in successful R&D activities plays a vital role when applying for public support, as governments often adopt a picking-the-winner strategy and hence might favour firms with previous success stories. Therefore, we include the patent stock (*PS*) in our regression. The patent stock enters into the regression as patent stock per employee to avoid potential multicollinearity with firm size (*PS/EMP*). Even though “not all inventions are patentable” and “not all inventions are patented” (Griliches, 1990, p.10), the patent stock is the best approximation we have for past innovation activities as data on previous R&D expenditures are not available. The patent stock information stem from the EPO dataset and are computed as a time series of patent applications with a 15% rate of obsolescence of knowledge capital, as is common in the literature (see e.g. Jaffe, 1986; Hall, 1990; Griliches and Mairesse, 1984): $PS_{i,t} = PS_{i,t-1} \times 0.85 + patentapplications_{i,t}$.

We also control for the degree of international competition by including an export quota in our analysis (*EXQU*). Firms that engage more heavily in foreign markets may be more innovative than others and, hence, more likely to apply for subsidies.

We further include the labor productivity as a covariate, measured as sales per employee, *LAB_PRO*, since high labor productivity is an important determinant for receiving public funds by the IWT.

Furthermore, we also control for past supported R&D projects. We include a dummy variable equal to one if the firms had already received an IWT grant in the 3 preceding years (*IWT_PAST3YRS*). Last but not least, industry dummies control for unobserved heterogeneity across sectors and time dummies capture macroeconomic shocks.

Timing of variables

As mentioned above, each wave of the survey covers a three-year period. In order to avoid endogeneity between the dependent variables and the covariates to the largest extent, we employ lagged values wherever possible. For instance, suppose the dependent variables are measured in period t. Then logEMP, PS/EMP, LAB_PRO and EXPORT are measured at the beginning of the survey period, i.e. in t-2.

The information on GP and FOREIGN is only available such that the question covers the whole 3-year period, i.e. t-2 to t. For instance, "Did your firm belong to a group during the period 2004-2006?" We consider AGE as truly exogenous and hence it is measured in period t.

Descriptive statistics

Table 2 shows the descriptive statistics of the variables of our sample. As we can see, almost all the variables are significantly different between the treated and the non-treated firms.

Table 2: Descriptive statistics

	Unsubsidized firms, N=4469		**Subsidized firms, N=292**		**Results on t-test on mean differences**
Variables	Mean	Std.dev.	Mean	Std.dev.	
			Covariates		
IWT_PAST3YRS	0.023	0.181	0.736	2.436	***
*PS/EMPL*1000*	1.340	8.254	13.456	27.277	***
EMPLOYMENT	3.484	1.298	4.690	1.884	***
FOREIGN	0.245	0.430	0.284	0.452	
EXPO	0.376	0.484	0.545	0.499	***
GP	0.466	0.499	0.664	0.473	***
AGE	3.113	0.777	3.153	0.889	
LABOR_PRO	5.197	0.867	5.279	0.701	*
Year T2	0.257	0.437	0.349	0.478	***
Year T3	0.426	0.494	0.257	0.438	***
			Outcome variables		
INT_RD_INT	0.894	5.322	7.579	12.694	***
RDEMP	2.646	9.960	18.287	21.980	***

For instance, firms receiving subsidies from the IWT are on average larger, more export oriented, belong to a group more often and have a higher labor productivity. Furthermore, they have had significantly more funded projects in the last three years and have a higher patent stock per employee. With regards to the outcome variables, funded firms have on average higher internal R&D intensity and more R&D employees. The econometric analysis in the next section will reveal to which extent these differences can be attributed to the treatment.

6. Econometric results

In order to apply the matching estimator as presented in the previous section, we first have to estimate a probit model so as to obtain the predicted probability of receiving an IWT grant to be employed as matching argument subsequently.

We can see in Table 3 that with the exception of the coefficients of the group, the age and the labor productivity variables, all the other coefficients are significantly different from zero and hence are important in driving the selection of into the local funding scheme.

Table 3: Probit estimation

	Coef.	Std. Err.
IWT_PAST3YRS	0.755***	0.084
*PS/EMPL*1000*	0.016***	0.002
LNEMP	-0.140	0.105
LNEMP2	0.042***	0.011
FOREIGN	-0.429***	0.099
EXPO	0.655***	0.103
GP	0.098	0.091
LNAGE	-0.073	0.047
LNLABOR_PRO	0.008	0.052
CONS	-1.750***	0.407
Test on joint significance on industry dummies		χ^2 (9) = 94,29***

Test on joint significance on time dummies	χ^2 (2) = 24,61***
Number of observations	4,761

As explained in the previous section, a necessary condition for the validity of the matching estimator is common support. In our case, 14 observations are lost because no common support could be found. In addition, 26 observations are dropped because of the capiler we impose on the maximum distance between neighbors. Hence, a total of 40 observations are deleted from the sample.

Table 4: Matching results on the full sample

	Selected control group, N=252		**Subsidized firms, N=252**		**p-value on the t-test on mean difference**
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
IWT_PAST3YRS	0.258	0.709	0.349	0.821	p=0.222
*PS/EMPL*1000*	7.932	20.092	8.354	20.032	p=0.831
LNEMP	4.302	1.876	4.359	1.678	p=0.745
LNEMP2	22.011	17.906	21.808	15.586	p=0.904
FOREIGN	0.262	0.441	0.262	0.441	p=1.000
EXPO	0.599	0.491	0.560	0.497	p=0.415
GP	0.544	0.499	0.623	0.486	p=0.103
LNAGE	3.099	0.873	3.085	0.860	p=0.866
LNLABOR_PRO	5.291	0.792	5.252	0.701	p=0.606
Outcome variables					
INT_RD_INT	3.151	10.373	6.883	12.140	p=0.001
RDEMP	8.061	18.254	17.627	21.603	p<0.001

As shown by Table 4, all our covariates are well balanced after the matching. Hence, we can conclude that our matching was successful and that we found a neighbor for each treated firm. The only variables where there still is a significant difference after the matching are our outcome variables. This difference can be attributed to the subsidy. The treatment effect in terms of internal R&D intensity is of 3.732 and for R&D employment of 9.567 percentage points. As a consequence, we can reject the null hypothesis of total crowding out effects. In line with previous findings on the effect of direct subsidies on firms in Belgium and other European countries, we can conclude that the IWT grants trigger investment into R&D in the recipient firms.

In the following sub-sections, we will proceed to a series of robustness checks, allowing us to enlighten some questions of interest for the policy maker.

Stability of treatment effects over time.

In times of a changing macroeconomic environment, it is useful for a policy maker to know whether the effect of a policy varies over time. As we use data from 2004, 2006 and 2008, it is interesting to test whether the treatment effects we observe are stable over this period. In other words, we want to see whether the effect of a subsidy receipt changes in period t+1 and t+2 compared to period t. In order to do so, we regress the respective outcome variables on the treatment indicator as well as on the interaction between the treatment indicator and the years t+1 and t+2.

Table 5: OLS regression testing for stability over time

	R&D employment			**Internal R&D intensity**		
	Coef.	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	11.822	2.881	0.000	4.297	1.414	0.003
IWT SUBSIDY IN T+1	-4.348	3.217	0.177	-2.152	1.513	0.156
IWT SUBSIDY IN T+2	-2.714	3.247	0.404	0.638	2.163	0.768
CONS	8.061	1.422	0.000	3.151	0.736	0.000
Tot number of observations	504			504		
Overall significance	F(3, 391)=7.97***			F(3, 391)=4.35***		

As shown by the results of Table 5, for both outcome variables under review, we do not find evidence that the treatment effect varies over time. The coefficients of the interaction terms between the treatment indicator and the time dummy for period t+1 as well as for period t+2 are insignificant. We can thus conclude that the effects of IWT subsidies on R&D employment and internal R&D investment remain stable over time and that there is no evidence for a decline of the effect of the policy measure under consideration over time.

The effect multiple subsidized projects at the same time

Since it is possible for one firm to benefit from more than one subsidized project during the same period, we test whether the treatment effects are larger for firms that have more than one subsidized project compared to firms that have only one subsidized project or whether this effect is declining with the number of projects. On average, each treated firm in our sample has 1.5 projects in a given year. Out of our 292 treated firms in the sample, 66% have only one project in a given year, 19% have two projects. One firm had 26 projects. Therefore, it is interesting to test whether the estimated treatment effect increases with the number of projects a firm has or whether we witness a decrease in the effect, indicating that supporting several projects in a same company would not be an efficient policy to pursue. In order to test this, we regress the estimated treatment effect on the number of projects a firm has. We considered non-linear specifications, as the concern would be that decreasing returns exist, that is, if more projects are granted at the same time, partial crowding out effects could emerge.

Table 6: Regression on the treatment effect on the number of supported projects

	R&D employment			**Internal R&D intensity**		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
Number of IWT subsidies	2.321	0.521	0.000	0.916	0.306	0.003

Cons	5.789	2.122	0.007	2.24	1.141	0.051
Tot number of observations		252			252	
Overall significance		F(1,208)=19.83***			F(1, 208)=8.96**	

However, we did not find any evidence of a non-linear relationship between the effect of the subsidies and the number of supported projects by a same firm, nor do we find evidence that granting multiple projects at the same time causes crowding out effects (see Table 6). The treatment effect grows linearly with the number of IWT projects granted. The magnitude of the slope is in line with the average treatment effect estimated above.

Evaluation of the treatment effects of "consecutive clients"

Funding agencies often consider previous experience (with R&D projects as well as with specific funding schemes) an important determinant in the selection process into a public subsidy scheme. As a consequence, some firms receive subsidies on a regular basis. It is thus interesting to evaluate whether this is a justified approach or whether one witnesses a decline of the subsidy effect over time if the same firm is a repetitive beneficiary. We thus test whether we observe a decline of the treatment effects if a firm gets funding repeatedly or whether the effects remain stable.

In order to test this, we regress the treatment effects of our respective outcome variables after the matching on the treatment indicator as well as on an interaction term composed by the treatment dummy and a dummy indicating whether a given firm has received a subsidy in the last 3 years, i.e. an IWT project that ended within the recent three years. As shown by Table 7, we do not find evidence that the treatment effect is smaller for firms that have received support for their R&D projects repeatedly. In other words, we do not find that the effect of a subsidy receipt decreases if a firm had completed an IWT project in the three years preceding the receipt of a new grant.

Table 7: Regression testing the treatment effect of "consecutive clients"

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT subsidy in t	9.273	2.001	0.000	3.417	1.087	0.002
*IWT subsidy in t*IWT subsidy in the last 3 years*	4.103	5.489	0.455	4.404	3.396	0.195
Cons	8.061	1.421	0.000	3.151	0.736	0
Tot number of observations		504			504	
Overall significance		F(2, 391)=11.95***			F(2, 391)=6.58***	

Taking subsidies from other sources into account

Since a firm that receives support from the Flemish government can also ask for, and receive, support from other public entities (i.e. form national or European entities), it is interesting to know for a policy maker if, and to which extent, the effect of one subsidy varies in case another one is received. To test this, we re-estimate our matching routine, but instead of only matching on the propensity score, we additionally match on a dummy variable indicating whether a firm received a subsidy from another entity (federal government or the EU) than the IWT. This means that an IWT recipient that has also received EU funding would only be matched with a firm that did not get an IWT subsidy, but received support from the EU. As displayed by Table 8, we find that our initial results hold. All the covariates are well balanced after the matching, with the exception of the outcome variables where a significantly positive result remains. The magnitude of the coefficients is, as expected, sensibly smaller than if one does not confound several sources of subsidies.

Table 8: Matching results on the full sample, controlling for other subsidies

	Selected control group, N=215		Subsidized firms, N=215		p-value on the t-test on mean difference
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
IWT_PAST3YRS	0.233	0.613	0.298	0.680	p=0.350
*PS/EMPL*1000*	5.629	17.357	6.191	17.597	p=0.767
LNEMP	4.508	1.917	4.318	1.656	p=0.337
LNEMP2	23.981	19.016	21.376	15.194	p=0.174
FOREIGN	0.293	0.456	0.247	0.432	p=0.339
EXPO	0.544	0.499	0.540	0.500	p=0.932
GP	0.628	0.484	0.623	0.486	p=0.930
LNAGE	3.143	0.857	3.075	0.852	p=0.465
LNLABOR_PRO	5.298	0.733	5.230	0.701	p=0.387
Outcome variables					
INT_RD_INT	3.788	10.642	6.780	12.171	p=0.015
RDEMP	9.142	17.742	17.635	21.746	p<0.001

The conclusions of stability over time, several funded projects at the same time and consecutive support hold as well if other subsidies are added as a matching criterion. The tables displaying the details of these results can be found in Appendix A2.

Dropping subsidized firms (other than IWT subsidies) from the control group

In the initial setting, we estimated the effect of an IWT treatment on our outcome variables, where the pool of potential controls consisted of all firms that did not receive an IWT subsidy. However, some of the potential controls might have received other subsidies which may confound the estimated IWT treatment effect. We have the possibility to control for the fact that firms may have received either a subsidy from the federal government and/or from the European Commission. We thus repeat our treatment effect estimation but exclude all firms that have gotten any other subsidy from the pool of potential controls. Before rerunning the matching routine, we have to re-estimate the probit model for this sample of firms (see Table 9).

Table 9: Probit estimation, dropping all the subsidized firms from sources other than the IWT

	Coef.	Std. Err.
IWT_PAST3YRS	1.343***	0.137
*PS/EMP*1000*	0.020***	0.002
LNEMP	-0.201*	0.112
LNEMP2	0.053***	0.012
FOREIGN	-0.415***	0.105
EXPO	0.676***	0.105
GP	0.051	0.096
LNAGE	-0.090*	0.050
LNLABOR_PRO	0.020	0.053
CONS	-1.718***	0.423
Test on joint significance on industry dummies		chi2(9) = 94.85***
Test on joint significnace on time dummies		chi2(2) = 20.39***
Number of observations		4,459

In this setting, 29 observations are lost because of our imposed caliper and 31 because of the common support condition. Hence, out the initial 292 treated firms, 232 remain in our sample. Our previous results are confirmed, and, as expected, the treatment effect is larger in magnitude since in this setting the counterfactual group is composed of firms that exclusively invest their private money (see Table 10).

Table 10: Matching results on the full sample, having exclusively non-subsidized firms as the control group

	Selected control group, N=232		**Subsidized firms, N=232**		**p-value on the t-test on mean difference**
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
iwt_past3yrs	0.185	0.451	0.190	0.464	p=0.928
ps_empl	6.533	18.296	6.955	0.018	p=0.823
lnemp	4.174	1.759	4.311	1.647	p=0.441

lnemp2	20.500	15.969	21.285	15.090	p=0.629
foreign	0.263	0.441	0.263	0.441	p=1.000
expo	0.608	0.489	0.586	0.494	p=0.673
gp	0.603	0.490	0.603	0.490	p=1.000
lnage	3.097	0.830	3.066	0.841	p=0.718
lnlabor_pro	5.104	0.771	5.252	0.713	p=0.057
Outcome variables					
int_rd_int	1.338	5.692	6.768	12.328	p<0.001
rdemp	5.153	17.172	17.476	22.028	p<0.001

As previously, the effects do not decline over time, and we do not witness smaller effects for firms that have several supported projects, respectively received support several times in a row (for the detailed results, refer to appendix A3).

Using only innovative firms

In the previous estimations, we allowed that non-innovating firms are in the pool of potential controls for the matching routine. This is based on the idea that, for instance, small firms rely heavily on IWT subsidies. In other words, it could be the case that a small firm could stop its R&D activities entirely if it would not be subsidized. In this robustness check, we drop the non-innovators from the control group. We thus assume that the firms would stay innovative even if they did not get a subsidy. Although this might underestimate the treatment effect to a certain extent, it is a good robustness check. It allows us to see if the magnitude of the treatment effect depends on the “zero observations” in the control group.

Before re-estimating the treatment effects, we have to re-estimate to probit estimation for our new sample (see Table 11). We see that the same covariates are significant as in the total sample.

Table 11: Probit estimation, only for innovative firms

	Coef.	Std. Err.
IWT_PAST3YRS	0.648***	0.084
*PS/EMPL*1000*	0.014***	0.002

LNEMP	-0.158	0.118
LNEMP2	0.038***	0.012
FOREIGN	-0.423***	0.109
EXPO	0.442***	0.128
GP	0.072	0.103
LNAGE	-0.070	0.052
LNLABOR_PRO	0.006	0.063
_CONS	-1.339***	0.488
Test on joint significance on industry dummies		chi2(9) = 64.04***
Test on joint significance on time dummies		chi2(2) = 15.16***
Number of observations		1,948

As shown by Table 12, the estimated treatment effects are basically the same as the ones reported above. This reaffirms our model specification as apparently the nearest neighbors that are drawn when using the full sample for the control group (i.e. including non-innovators) are typically innovators.

Table 12: Matching results, of innovative firms only

	Selected control group, N=262		**Subsidized firms, N=262**		**p-value on the t-test on mean difference**
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
IWT_PAST3YRS	0.305	0.726	0.321	0.766	p=0.839
*PS_EMPL*1000*	10.053	23.261	10.500	23.534	p=0.851
LNEMP	4.387	1.648	4.426	1.707	p=0.818
LNEMP2	21.949	15.291	22.490	16.121	p=0.733
FOREIGN	0.271	0.445	0.263	0.441	p=0.866
EXPO	0.595	0.492	0.573	0.496	p=0.648
GP	0.595	0.492	0.634	0.483	p=0.442
LNAGE	3.149	0.855	3.091	0.860	p=0.507
LNLABOR_PRO	5.164	0.714	5.260	0.708	p=0.188
Outcome variables					
INT_RD_INT	3.235	8.328	6.745	11.622	p<0.001
RDEMP	8.145	13.390	17.220	20.670	p<0.001

As previously, the effects do not decline over time, and we do not witness smaller effects for firms that have several supported projects, respectively received support several times in a row (for the detailed results of the robustness checks and the descriptive statistics of this sample, refer to Appendix A4).

Evaluating the KMO recipients separately

Between 2004 and 2010, about two thirds of all IWT grants were handed out under the label of the "KMO programma", a subsidy scheme designed for small and medium-sized enterprises. Given that stark presence of a single scheme within the landscape of programs, we performed the estimations reported above separately for these subsidy recipients. Before re-estimating our matching routine, we will re-estimate the probit model, providing us the propensity score to be used as matching criteria. As displayed by Table 13, the same variables are significant in driving the selection into the KMO program than into a general subsidy scheme.

Table 13: Probit estimation, only KMO recipients

	Coef.	Std. Err.
KMO_PAST3YRS	0.868***	0.125
*PS/EMP*1000*	0.010***	0.003
LNEMP	0.388**	0.176
LNEMP2	-0.056**	0.023
FOREIGN	-0.890***	0.207
EXPO	0.620***	0.131
GP	-0.026	0.131
LNAGE	-0.050	0.063
LNLABOR_PRO	-0.077	0.067
CONS	-2.046***	0.520
Test on joint significance on industry dummies		chi2(9) = 43.21***
Test on joint significance on time dummies		chi2(9) = 17.10***
Number of observations		4,761

As shown by Table 14, the estimated treatment effects are in line with those reported when considering both IWT schemes cumulated. After the matching, all the covariates are well balanced with the exception of the outcome variables, where positive significant differences exist due to the receipt of a grant. For details on descriptive statistics and robustness checks with regards to stability over time, several supported projects or persistent clients, refer to appendix A5.

Table 14: Matching results, KMO recipients only

	Selected control group, N=114		**Subsidized firms, N=114**		**p-value on the t-test on mean difference**
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
KMO_PAST3YRS	0.114	0.394	0.149	0.426	p=0.530
*PS/EMPL*1000*	6.452	18.126	6.440	18.112	p=0.996
LNEMP	3.414	1.040	3.330	1.051	p=0.556
LNEMP2	12.726	7.687	12.183	6.707	p=0.582
FOREIGN	0.044	0.206	0.035	0.185	p=0.743
EXPO	0.614	0.489	0.553	0.499	p=0.362
GP	0.333	0.473	0.342	0.477	p=0.892
LNAGE	3.074	0.845	3.020	0.796	p=0.628
LNLABOR_PRO	5.020	0.833	5.007	0.609	p=0.897
Outcome variables					
INT_RD_INT	1.990	5.472	6.625	12.224	p<0.001
RDEMP	4.503	10.799	18.170	22.121	p<0.001

We thus confirm our earlier findings of input additionality in the KMO program. Furthermore, the treatment effects are somewhat lager in the case of KMO subsidies than in the full sample using also other schemes as treatment. This finding was expected, since one would suppose that the effect of a grant is higher for an SME than for a larger firm in terms of its relative impact on total R&D efforts of the firm. Furthermore, the KMO subsidies cover 10%

more of the cost of an R&D project for small firms than the other grants. The results are thus in line with what one would except to observe.

7. Macroeconomic impact of local R&D policies on the Flemish economy

What do these effects mean in terms of economic magnitude, however?

In order to put the treatment effect into context, we conduct a 'back of the envelope' calculation on macroeconomic effects of the IWT subsidies.[7] In particular, we are interested in knowing how many (R&D) jobs these public grants create. In our sample, the R&D employment intensity amounts to 8% for the firms composing the selected control group (i.e. the treated firms, if they would not have gotten a subsidy).

At the sample median[8], total employment equals 49 employees, say 50 for easier calculation. Thus, in the counterfactual situation, a treated company would employ about 4 R&D employees (8% R&D employment intensity).

The treatment effect of a subsidy receipt concerning R&D employment intensity (i.e. the ratio of R&D employees to total employment) amounts to about 9.567 percentage points, that is, each treatment in our context creates or secures about 5 R&D jobs.[9]

What does this exactly correspond to in our case of Northern Belgium?

On average, the recipient firms have 1.5 IWT projects in a given year. In total, the IWT granted 3,019 projects with a total subsidy value of € 628 million between 2004 and 2010. As

[7] The following calcualations refer to the first analysis, namely the entire sample (innovative and non-innovative firms), containing KMO and the R&D subsidy schemes.

[8]We take the median rather than the mean because of the skewness of the employment distribution.

[9] Average number of R&D employees in the selected control group : 50*0.08 = 4
If treatment is received, increase of 9.647 percentage points. Hence: 50*(0.08+0.096) = 8.8 ~ 9
Additional jobs created or secured: 9 – 4 = 5

each company in our sample has on average 1.5 project in a given year, the estimated 5 R&D jobs are created 2,012 times in total (= 3,019/1.5). Thus, in total the subsidies create 10,060 (R&D) jobs (2,012 * 5). Note that our treatment effects calculation is based on annual data. As the average project duration is about 20 months, the subsidies create a total sum of 16,800 (10,060 * (20/12)) person-years of R&D employment in the Flemish economy. Given that this result is achieved with a total budget of € 628 million of public budget, society pays about € 37,000 per created R&D employment per person per year.

From the Flemish R&D survey, we calculated the average cost of an R&D workplace. In other words, we calculated the R&D personnel cost, including the employers' social security contribution and the average annual working expenses for maintaining an R&D workplace. According to the R&D survey 2008, this cost amounts to € 64,000 on average. Thus, we can conclude that € 37,000 are sponsored by public funding, and the companies' average contribution amount to roughly € 27,000. Note that this is a back of the envelope calculation based on averages, and that we do not want to stress that this could be evidence on partial crowding out. As the subsidy rate is on average 40% of total project cost, one could expect that the industry share in the total work place cost should be higher than € 27,000. However, one has to keep in mind that we only take into account the firm's costs linked to R&D employment, disregarding other expenses like e.g. lab equipment and similar assets a firm has to invest in when conducting R&D projects. Such costs have not been taken into account in our ballpark figure.

8. Conclusion

The present paper presents new microeconometric evidence on the question of input additionality for a local Belgium subsidy scheme. While many papers have analyzed the impact of subsidies on firms' innovative behavior, there is no econometric evidence on how this effect might change over time or how it might be affected if several projects are supported at the same time respectively if the firm gets support on a regular basis. This paper allows answering these questions, revealing important information for policy makers.

In line with the literature, we can reject the null hypothesis of total crowding out. Our subsequent robustness checks further allow us to conclude that we do not witness varying effects over time and that multiple grants at the same time do not cause crowding out effects. We can also conclude that there is no declining effect if firms get subsidies recurrently. We repeat these three robustness checks on stability over time, several supported projects at the same time and recurrent clients for a sample including only innovative firms, for a sample considering only the SME subsidy program, for a sample where we take subsidized firms from other funding agencies out of the control group and for a sample where in addition on matching only on the propensity score we also match on the probability of getting funds from other funding agencies. Our conclusions hold for each of these settings.

Finally, we estimate the macroeconomic impact of these Flemish subsidies on the local economy in terms of (R&D) jobs that are created. On average, one supported project creates 5 (R&D) jobs, out of which roughly € 37,000 are paid for by the public and € 27,000 by the firm. Keeping in mind that this figure is based only on the cost directly related to an employee and not including any equipment costs a firm encounters when hiring an additional person, our findings do not suggest crowding out. To the contrary, we can conclude that the current Flemish innovation policy does achieve its goal of enhanced R&D investment and job creation. Indeed, since we found that subsidies do increase the number of R&D employees, we can conclude that the additional investment in R&D does not just go into increased wages of the R&D personnel.

In many previous studies, information on the number of employees allowing to draw this conclusion is often missing.

A clear limitation of the paper is the fact that we do not have panel data and can thus not use methods like for instance difference-in-difference, respectively that we could not find a valid instrument allowing us to address the selection bias problem while controlling for the selection of unobservables. In our current set-up, we have to assume that all the important characteristics driving the selection into the Flemish local subsidy scheme are observed.

References:

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

Almus, M. and D. Czarnitzki (2003), The effects of public R&D subsidies on firms' innovation activities: the case of Eastern Germany, *Journal of Business and Economic Statistics* 21(2), 226-236.

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

Arrow, Kenneth J. (1962), Economic Welfare and the Allocation of Resources for Invention, in Richard R. Nelson (ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors*, National Bureau of Economic Research, Conference Series, Princeton: Princeton University Press, pp. 609-625.

Arrow, Kenneth J. and Robert C. Lind (1970), Uncertainty and the Evaluation of Public Investment Decisions, *The American Economic Review*, 60, 364-378.

Arrow, Kenneth J. (1996), The Economics of Information: An Exposition, *Empirica*, Vol. 23, No. 2, pp. 119-128.

Arrow, Kenneth J. (1999), Information and the Organization of Industry, in Graciela Chichilnisky (ed.), *Markets, Information, and Uncertainty*. Essays in Economic Theory in Honor of Kenneth J. Arrow, Cambridge: Cambridge University Press, pp. 19-25.

Busom, I. (2000), An empirical evaluation of the effects of R&D subsidies, *Economics of Innovation and New Technology* 9(2), 111-148.

Czarnitzki, D. and K. Hussinger (2004), The Link between R&D Subsidies, R&D Spending and Technological Performance, *ZEW Discussion Paper No. 4-56*, Mannheim.

Czarnitzki, D. and C. Lopes Bento (2011a), Evaluation of Public R&D Policies: A Cross-Country Comparison, *World Review of Science, Technology and Sustainable Development*, forthcoming.

Czarnitzki, D. and C. Lopes Bento (2011b), Innovation Subsidies: Does the Funding Source Matter for Innovation Intensity and Performance? Empirical Evidence from Germany, *ZEW Discussion Paper No. 11-053,* Mannheim.

Czarnitzki, D. and H. Hottenrott (2011), R&D Investment and Financing Constraints of Small and Medium-Sized Firms, *Small Business Economics,* 36(1), 65-83.

David, P.A., B.H. Hall and A.A. Toole (2000), Is public R&D a complement or substitute forprivate R&D? A review of the econometric evidence, Research Policy 29(4-5), 497-529.

Dehejia, R.H. and S. Wahba (1999), Causal effects in nonexperimental studies: reevaluating the evaluation of training programs, Journal of the American Statistical Association 94, 1053-1062.

Dixit, A.K. and R.S. Pindyck, Investment under Uncertainty, *Princeton Univ. Press*, Princeton, NJ.

Duguet E. (2004), Are R&D subsidies a substitute or a complement to privately funded R&D? Evidence from France using propensity score methods for non experimental data, Revue d'EconomiePolitique 114(2), 263-292.

Garcia, A. and P. Mohnen (2010), Impact of government support on R&D and innovation, *UNU-MERIT Working Paper Series 034*, United Nations University, Maastricht Economic and social Research and training centre on Innovation and Technology, Maastricht.

Gerfin M. and M. Lechner (2002), A Microeconometric Evaluation of Active Labour Market Policy in Switzerland, The Economic Journal 112, 845 -893.

González, X., Jaumandreu, J. and Pazó, C. (2005), Barriers to innovation and subsidy effectiveness, RAND Journal of Economics 36(4), 930-949.

Griliches, Z. and J. Mairesse (1984), Productivity and R&D at the firm level, in: R&D, *Patents and Productivity*, Griliches Z (ed.). University of Chicago Press: Chicago, IL; 339–374

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

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

Hall, B.H. and J. Van Reenen (2000), How effective are fiscal incentives for R&D? *Research Policy*, 29, 449-469.

Hall, B.H., (2002), The financing of Research and Development, *Oxford Review of Economic Policy*, 18, 35-51.

Heckman, J. J., H. Ichimura and P. Todd (1997), Matching as an econometric evaluation estimator: evidence from evaluating a job training program, *Review of Economic Studies* 64(4), 605-654.

Heckman, J.J., H. Ichimura and P. Todd (1998a), Matching as an econometric evaluation estimator, *Review of Economic Studies* 65(2), 261-294.

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

Heckman, J. J., R. J. Lalonde and J. A. Smith (1999), The economics and econometrics of active labour market programs, in: A. Aschenfelter and D. Card (eds.), *Handbook of Labour Economics*, Amsterdam, 3, 1866-2097.

Holland, P.W. (1986), Statistics and Causal Inference, *Journal of the American Statistical. Association* 81, 945–960.

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

Imbens, G.W. (2000), The role of the propensity score in estimating dose-response functions, *Biometrika* 87, 706–710.

Imbens, G.W. and J.M. Wooldridge (2009), Recent Developments in the Econometrics of Program Evaluation, *Journal of Economic Literature* 47, 5-86.

Jaffe, A.B. (1986), Technological opportunity and spillovers of R&D: evidence from firm’s patent, profits, and market value, American Economic Review 76 (5), 984–1001.

Lach, S. (2002), Do R&D subsidies stimulate or displace private R&D? Evidence from Israel, *Journal of Industrial Economics* 50(4), 369-390.

Lamberton, D. M. (1996), ‘Introduction: ‘Threatened Wreckage’ or New Paradigm?’, in Donald M. Lamberton (Ed.), *The Economics of Communication and Information*, Cheltham UK and Brookfield US: Edward Elgar, pp. xiii-xxviii.

Larosse, J. (2001), Conceptual and Empirical Challenges of Evaluating the Effectiveness of Innovation Policies with ‘Behavioural Additionality’, Case of IWT R&D Subsidies, IWT-Flanders, Belgium.

Lechner, M. (1999), Earnings and employment effects of continuous off-the-job training in East Germany after reunification, *Journal of Business and Economics Statistics* 17, 74-90.

Lechner, M. (2000), An evaluation of public sector sponsored continuous vocational training in East Germany, *Journal of Human Resources* 35, 347-375.

Lechner, M. (2001), Identification and Estimation of Causal Effects of Multiple Treatments under the Conditional Independence Assumption, in M. Lechner and F. Pfeiffer (eds.), *Econometric Evaluation of Labour Market Policies*, Physica, Heidelberg, 43-58.

Nelson, R.R. (1959), The Simple Economics of Basic Scientific Research, *Journal of Political Economy* 49, 297-306.

Nelson, R.R. (1959), The Simple Economics of Basic Scientific Research, *Journal of Political Economy* 49, 297-306.

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

OECD/Eurostat (2005), *Guidelines for Collecting and Interpreting Innovation Data – the Oslo Manual*, 3rd edition, Paris.

Rosenbaum, P.R. and D.B. Rubin (1983), The central role of the propensity score observational studies for causal effects, *Biometrica* 70, 41-55.

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

Rubin, D.B. (2008), For objective causal inference, design trumps analysis,*The Annals of Applied Statistics* 2(3), 808-840.

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

Smith, J.A. and P. E. Todd (2005), Does Matching Overcome LaLonde's Critique of Non experimental Estimators, *Journal of Econometrics* (125), 305-353.

Takalo, T., Tanayama T. and O. Toivanen (2011), Estimating Benefits of Targeted R&D Subsidies, Helsinki, mimeo.

Appendix A1: Firm repartition

Table A 1: Industry structure

Industry	**Number of firms**
1	364
2	213
3	346
4	400
5	415
6	193
7	1400
8	738
9	415
10	277
Total	**4761**

Table A 2: Size distribution

Size class distribution	**Number of firms**
Min. - 4	135
5 - 9	552
10 - 49	2,389
50 - 249	1,216
250 – max.	469
Total	**4761**

Appendix A2: Detailed results if the receipt of other grants are added as matching criteria

Table A 3: Regression testing for stability over time

	R&D employment			Internal R&D intensity		
	Coef.	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	9.769	2.972	0.001	3.176	1.491	0.034
IWT SUBSIDY IN T+1	-3.696	3.537	0.297	-1.870	1.574	0.236
IWT SUBSIDY IN T+2	-2.134	3.471	0.539	1.115	2.320	0.631
CONS	9.633	1.532	0.000	3.865	0.902	0.000
Tot number of observations	430			430		
Overall significance	F(3, 326) = 4.79***			F(3, 326) = 2.22**		

Table A 4: Regression on the treatment effect on the number of supported projects

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
NUMBER OF IWT SUBSIDIES	2.761	0.771	0.000	1.180	0.459	0.011
CONS	3.622	2.438	0.139	1.044	1.278	0.415
Tot number of observations	215			215		
Overall significance	F(1, 183) = 12.81***			F(1, 183) = 6.61**		

Table A 5: Regression testing for the treatment effect of "consecutive clients"

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	7.613	2.159	0.000	2.518	1.228	0.041
*IWT SUBSIDY IN T*IWT SUBSIDY IN THE LAST 3 YEARS*	7.595	7.853	0.334	7.758	5.053	0.126
CONS	9.633	1.530	0.000	3.865	0.901	0
Tot number of observations	430			430		
Overall significance	F(2, 326) = 7.28***			F(2, 326) = 3.63**		

Appendix A3: Detailed results if grant receipts from sources other than the IWT are taken out of the control group

Table A 6: Regression testing for stability over time

	R&D employment			Internal R&D intensity		
	Coef.	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	14.882	3.449	0.000	5.764	1.446	0.000
IWT SUBSIDY IN T+1	-4.720	3.315	0.155	-1.799	1.408	0.202
IWT SUBSIDY IN T+2	-2.712	3.626	0.455	1.291	2.348	0.583
CONS	5.153	1.934	0.008	1.338	0.626	0.033
Tot number of observations	464			464		
Overall significance	F(3, 368)=8.46***			F(3, 368)=8.56***		

Table A 7: Regression on the treatment effect on the number of supported projects

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
NUMBER OF IWT SUBSIDIES	2.532	0.608	0.000	1.023	0.439	0.021
CONS	8.438	2.233	0.000	3.861	1.168	0.001
Tot number of observations	232			232		
Overall significance	F(1, 195)=17.33***			F(1, 195)=5.42**		

Table A 8: Regression testing for the treatment effect of "consecutive clients"

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	12.236	2.502	0.000	5.323	1.088	0.000
*IWT SUBSIDY IN T*IWT SUBSIDY IN THE LAST 3 YEARS*	4.010	12.133	0.741	4.949	6.729	0.462
CONS	5.153	1.931	0.008	1.338	0.625	0.033
Tot number of observations	464			464		
Overall significance	F(2, 368)=12.23***			F(2, 368)=12.77***		

Appendix A4: Descriptive statistics and robustness checks for the innovative only sample

Table A 9: Descriptive statistics, only innovative firms

	Unsubsidized firms, N=1656		Subsidized firms, N=292		Results on t-test on mean difference
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
IWT_PAST3YRS	0.054	0.281	0.736	2.436	***
*PS/EMPL*1000*	2.528	11.366	13.457	27.277	***
LNEMP	3.890	1.399	4.690	1.884	***
LNEMP2	17.089	12.137	25.535	19.005	***
FOREIGN	0.290	0.454	0.284	0.452	
EXPO	0.434	0.496	0.545	0.499	***
GP	0.557	0.497	0.664	0.473	***
LNAGE	3.136	0.838	3.153	0.889	
LNLABOR_PRO	5.284	0.791	5.279	0.701	
T2	0.239	0.427	0.349	0.478	***
T3	0.345	0.476	0.257	0.438	**
Outcome variables					
INT_RD_INT	2.413	8.533	7.579	12.694	***
RDEMP	6.851	14.916	18.287	21.980	***

Table A 10: Regression testing for stability over time

	R&D employment			Internal R&D intensity		
	Coef.	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	11.064	2.678	0.000	3.789	1.224	0.002
IWT SUBSIDY IN T+1	-4.012	3.038	0.188	-1.875	1.390	0.178
IWT SUBSIDY IN T+2	-2.030	3.050	0.506	1.327	2.022	0.512
CONS	8.145	1.267	0.000	3.235	0.574	0.000
Tot number of observations	524			524		
Overall significance	F(3, 386) = 8.60***			F(3, 386) = 5.10***		

Table A 11: Regression on the treatment effect on the number of supported projects

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**

NUMBER OF IWT SUBSIDIES	1.297	0.587	0.028	0.321	0.476	0.500
CONS	6.867	1.893	0.000	2.964	1.099	0.008
Tot number of observations	262			262		
Overall significance	F(1, 214) = 4.88**			F(1, 214) = 0.46		

Table A 12: Regression on the treatment effect of "consecutive clients"

	R&D employment			Internal R&D intensity		
R&D employment	**Coef.**	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
IWT SUBSIDY IN T	8.663	1.822	0.000	3.141	0.943	0.001
*IWT SUBSIDY IN T*IWT SUBSIDY IN THE LAST 3 YEARS*	6.349	5.551	0.253	5.693	3.462	0.101
CONS	8.145	1.265	0.000	3.235	0.573	0.000
Tot number of observations	524			524		
Overall significance	F(2, 386) = 13.21***			F(2, 386) = 8.01***		

Appendix A5: Descriptive statistics and robustness checks for the KMO only sample

Table A 13: Descriptive statistics, only KMO recipients

	Unsubsidized firms, N=4638		**Subsidized firms, N=123**		**Results on t-test on mean difference**
Variables	Mean	Std.dev.	Mean	Std.dev.	
Covariates					
KMO_PAST3YRS	0.015	0.131	0.301	0.789	***
*PS/EMPL*1000*	1.924	10.428	8.112	20.726	***
LNEMP	3.565	1.379	3.312	1.045	***
LNEMP2	14.607	11.501	12.051	6.694	***
FOREIGN	0.254	0.435	0.033	0.178	***
EXPO	0.382	0.486	0.528	0.501	***
GP	0.482	0.500	0.350	0.479	**
LNAGE	3.119	0.785	2.999	0.783	*
LNLABOR_PRO	5.207	0.863	5.003	0.597	***
YEAR T2	0.260	0.439	0.350	0.479	**
YEAR T3	0.419	0.494	0.260	0.441	***
Outcome variables					
INT_RD_INT	1.152	5.929	7.052	12.317	***
RDEMP	3.191	10.965	19.201	22.661	***

Robustness checks for KMO recipients

Table A 14: Regression on stability over time

	R&D employment			**Internal R&D intensity**		
	Coef.	**Robust std. Err.**	**P>|t|**	**Coef.**	**Robust std. Err.**	**P>|t|**
KMO SUBSIDY IN T	19.482	4.279	0.000	6.425	1.974	0.001
KMO SUBSIDY IN T+1	-10.493	5.238	0.046	-4.801	2.163	0.028
KMO SUBSIDY IN T+2	-7.273	4.871	0.137	-0.223	3.455	0.949
CONS	4.503	1.174	0.000	1.990	0.554	0.000
Tot number of observations	228			228		
Overall significance	F(3, 210)=12.42***			F(3,210)=4.94**		

Table A 15: Regression on the treatment effect on the number of supported projects

R&D employment	R&D employment			Internal R&D intensity		
	Coef.	Robust std. Err.	P>|t|	Coef.	Robust std. Err.	P>|t|
NUMBER OF KMO SUBSIDIES	6.503	2.283	0.005	4.393	1.782	0.015
CONS	5.167	3.669	0.162	-1.106	2.290	0.630
Tot number of observations	114			114		
Overall significance	F(1, 160)=8.11***			F(1, 160)=6.08**		

Table A 16: Regression testing for the treatment effect of "consecutive clients"

R&D employment	R&D employment			Internal R&D intensity		
	Coef.	Robust std. Err.	P>|t|	Coef.	Robust std. Err.	P>|t|
KMO SUBSIDY IN T	13.391	2.356	0.000	4.377	1.272	0.001
*KMO SUBSIDY IN T*IWT SUBSIDY IN THE LAST 3 YEARS*	10.475	18.404	0.570	9.820	10.037	0.329
CONS	4.503	1.172	0.000	1.990	0.553	0.000
Tot number of observations	228			228		
Overall significance	F(2, 210)=16.75***			F(2, 210)=6.84***		