# Direct and Cross Scheme Effects in a Research and Development Subsidy Program*

Hanna Hottenrott[a,b,d], Cindy Lopes-Bento[b,c,d] and Reinhilde Veugelers[b,e]

*a) TUM School of Management, Technische Universität München*
*b) Dept. of Managerial Economics, Strategy and Innovation, K.U.Leuven*
*c) School of Business and Economics, Maastricht University*
*d) Centre for European Economic Research (ZEW), Mannheim*
*e) Bruegel, Brussels*

December 2016

**Abstract**

Research and product or process development are two distinct, yet complementary innovation activities. Making use of a specific grant-based policy design that explicitly distinguishes between research projects, development projects, and mixed R&D projects, this study estimates the direct and cross scheme effects on both research and development investments of recipient firms. Positive cross scheme effects can be expected when research and development activities are complementary and financing constraints are more binding for research than for development projects. The results show that while research grants yield positive direct effects on net research spending as well as positive cross effects on development, development grants are less effective for stimulating development expenditures. The positive effect of development grants on overall R&D stems from cross effects of development grants on research expenditures. These results suggest a higher priority for subsidies targeting research projects.

Keywords: R&D, Complementarity, Research Subsidies, Development Subsidies, Innovation Policy
JEL-Classification: H23, O31, O38

Contact details:
Hanna Hottenrott, TUM School of Management, Technische Universität München, Arcisstraße 21, 80333 München, Germany. hanna.hottenrott@tum.de
Cindy Lopes-Bento, Maastricht University, School of Business and Economics, Tongersestraat 53, 6211 LM Maastricht, The Netherlands. c.lopes-bento@maastrichtuniversity.nl
Reinhilde Veugelers, K.U.Leuven, Department of Managerial Economics, Strategy and Innovation, Naamsestraat 69, 3000 Leuven, Belgium. reinhilde.veugelers@kuleuven.be

***Acknowledgements:** The authors thank IWT for providing the subsidy data and to the Centre for R&D Monitoring (ECOOM) for access to the R&D Survey data. The authors would also like to thank seminar participants at KU Leuven, University of Hohenheim, Nottingham University Business School, TUM School of Management, University of Linz, and Maastricht University. They also thank participants at the SEEK2014 conference, the 5th ZEW/MaCCI Conference on Economics of Innovation and Patenting, the CONCORDi2013 Conference, the 2014 IIOC, especially Saul Lach and Pilar Benito, the DRUID15 conference, the EARIE 2015 conference, the 2015 Conference of the *Verein für Socialpoliktik* and the SEEK2015 conference for useful comments. Lopes-Bento gratefully acknowledges financial support by the National Research Fund, Luxembourg, cofounded under the Marie Curie Actions of the European Commission (FP7-COFUND). Veugelers acknowledges support from FWO (G.08512) and KU Leuven (GOA/12/003).

# 1. Introduction

Endogenous growth theory has long singled out public subsidies to R&D as one of the main policy tools to address market failure related to research and development investments (Aghion and Howitt 1998; Howitt 1999; Segerstrom 2000). It is therefore not surprising that R&D subsidies are one of the largest and fastest-growing forms of industrial aid in developed countries (Nevo 1998; Pretschker 1998). A comprehensive literature has investigated the effects of public subsidies on private R&D spending. Although this literature by now provides substantial evidence that subsidies can be an effective tool to trigger additional R&D in the private sector, the cost-efficiency of providing such schemes is still under debate (Takalo et al. 2013a, b). Moreover, little is known about the responsiveness of the different activities within the R&D process to public subsidies.

R&D subsidies are often designed as direct grants and affect two related, but distinct activities, namely research ('R') and development ('D'). Research activities show fundamentally different characteristics from development activities as research typically involves more tacit knowledge, higher intangibility, greater outcome uncertainty, and larger distance to the market. These features explain the different extent of market failure associated with research versus development investments. Appropriability tends to be weaker for research investments compared to development because research typically involves early-stage activities with a wider set of possible applications and hence higher knowledge spillovers and higher expected social returns (e.g. Akcigit et al. 2013). Moreover, information asymmetries are typically more severe for such early-stage investments leading to more binding financing constraints for research than for development projects (Czarnitzki et al. 2011).

At the same time, research and development are interdependent activities. Product and process development often depends on the outcome of research activities. Firms may need to do (basic) research in order to understand how to solve problems of a more applied nature and be more effective in development activities. Quoting Rosenberg (1990, p. 171): "[…] a basic research capability is essential for evaluating the outcome of much applied research and for perceiving its possible implications."

If research and development have different characteristics that affect the wedge between their private and social returns and invoke different financial constraints, an optimal subsidy policy should be tailored to these different characteristics. Moreover, when different subsidy schemes are set for research and for development, their interdependencies should be taken into account. Although recent theoretical modelling on endogenous growth through basic and applied research advocates public policy that targets basic research directly (Akcigit et al. 2013), previous empirical studies on the impact of public R&D grants generally do not distinguish between (basic) research and applied development grants nor do they differentiate between the impact on research versus development activities. This can mainly be attributed to a lack of access to information on the nature of the project which is being subsidized as well as on how much private money is spent by firms on each of these activities. One exception is a study on Norwegian innovation policy by Clausen (2009). Clausen applies a taxonomy that distinguishes between projects that are "close to the market" and projects that are "far from the market." The author finds that while grants received for projects far from the market stimulate additional research spending, those received for projects close to the market are more likely to substitute firms' own spending on development. These results suggest that the extent to which public co-funding of R&D projects induces additional private investments depends on the type of subsidized project. However, while this taxonomy takes into consideration the stage of advancement of the R&D process, it does not unambiguously separate research and development activities. Furthermore, the classification of R&D subsidies used in this study is based on a taxonomy defined by the author rather than on the policy design of the program.

In this paper, we investigate the additionality effects of targeted research and development grants on both research and development spending. This allows testing not only for different effects from the different types of grants, but also to test for any cross-effects from research grants on development spending and vice versa. The analysis presented in this paper thus addresses the research question of whether targeted schemes induce the desired outcomes. Further, we investigate at which stage of the R&D process public co-funding through grant-based subsidies is most effective in inducing additional investments in the recipient firms. In addition, by comparing targeted research and development grant programs to a general R&D scheme, we analyze which program design is more effective.

To address this research agenda, we investigate a project-based innovation policy implemented in the Belgian region of Flanders, which explicitly provides different schemes for research projects, development projects, and mixed R&D projects. We analyze data on the population of publicly co-financed projects over the period 2000 to 2011. During the first five years of that period mainly mixed-scheme projects had been co-funded, while in later years the policy shifted to primarily targeted programs for research or development. We match the subsidy data with the Belgian part of the OECD/Eurostat survey, which comprises information on firms' own R&D investment, split into its research and development component in order to estimate direct and cross scheme effects.

This study contributes to the existing literature and informs the current academic and policy debate on R&D subsidies in several ways. First, the ability to distinguish research from development grants allows us to assess the direct effects of research grants on research expenditures and of development grants on development expenditures. It also allows us to test for cross scheme effects in which a research (development) grant triggers additional development (research) expenditures. Third, information on project duration and the amount received allows us to estimate both direct and cross effects on "*net*" expenditures. That implies that the following analysis not only tests for full crowding out but also for partial crowding out.

The results confirm previous studies by showing positive additionality on private R&D spending from a grant-based subsidy program. While most previous studies conclude such additionality for the gross spending, we can conclude that the net spending also increases due to the public support. More importantly, the results further clarify these insights by showing that while research grants induce additional net research spending together with significant positive cross effects on development spending, there are little direct effects of development grants on development spending. Development grants, however, do generate positive cross scheme effects on research investments. Overall, the results suggest that the impact of the R&D policy increased under the targeted schemes compared to the mixed grant scheme design.

## 2. The policy design: Why targeted subsidy schemes?

The general rationale for government support of R&D rests on the presumption that private sector incentives (or possibilities) to invest in R&D are insufficient from a social welfare point of view. Governments typically complement private sector R&D by investing in the public research sector such as universities or by offering R&D contracts that tend to be more mission-oriented (David and Hall 2000). Additionally, governments provide R&D funding to the private sector firms via direct grants that contribute directly to the firms' costs of an R&D project. In most OECD countries, this is a major instrument to stimulate private innovation activities. While such grants typically do not distinguish between research and development, this section discusses why it may be optimal to target grant-based subsidy schemes towards certain project types.

R&D projects comprise different types of activities. Following the definition of the OECD's Frascati Manual, basic research primarily aims at acquiring new knowledge not necessarily with applications in mind, while applied research is an activity directed toward a specific objective. Research projects can be characterized by a high degree of outcome uncertainty and by being 'far from the market' without directly targeting commercialization opportunities. Yet, they typically create the foundation for future product or process development projects (see e.g., Mansfield et al. 1971). As research involves early-stage technologies, the new knowledge is often tacit and therefore more difficult to fully appropriate by the creator (Arrow 1962; Usher 1964). Because of the higher spillovers, economic theory suggests a larger gap between the social and private rates of returns for research activities compared to development activities. Development projects, on the other hand, aim at commercializing inventions. As the development trajectory is often more focused and builds on earlier research investments, it is less prone to spillovers when compared to research. In addition, because development projects are closer to the actual implementation of an invention or the introduction of a new product to the market, firms will typically protect their "close-to-the-market" innovations through formal and informal IP strategies (Cassiman and Veugelers 2002).

Beyond differences in spillovers and appropriability, research and development activities are different in their risk and uncertainty profile. Karlsson et al. (2004) promote the idea that research is a more discontinuous process, which may or may not result in solutions, whereas development is a more continuous search for solutions within an existing set of ideas. Such differences in risk and uncertainty translate into different sensitivities of research versus development investments to imperfections in the financial markets. Czarnitzki et al. (2011) find in a sample of Flemish firms that research investments are much more dependent on firms' internal financial resources than development projects, pointing to more binding financing constraints for research.

Given this heterogeneity of activities within the R&D process, it seems reasonable for policy makers to consider these specificities when designing innovation policy tools. With more difficult appropriability conditions and higher outgoing spillovers, costly or even constrained access to external finance for research activities, divergence between private and social returns and financial market failures are likely to be larger for research than for development activities. The optimal subsidy rate for research projects should consequently be higher than for development projects and the expected additionality effects from subsidizing both type of activities may differ.

### *2.1 Direct additionality*

From a public policy point of view, the major objectives of R&D grants are to compensate firms for the social return to their R&D investments and to ease financial market frictions that increase the private costs of financing R&D (Wallsten 2000, David et al. 2000). The effect of the government's funding schemes is therefore such that it reduces the share of costs of the R&D project to be borne by the firm and thereby affects the amount of financing that it needs to raise. Holding expected gains constant and in the absence of crowding out, lower costs due to public grants will result in a higher expected rate of return, thereby increasing incentives to invest in R&D. This positive cash effect will be larger the higher the initial cost of capital (Hottenrott and Peters, 2012). Expression (1) illustrates the different components of the cost of research and development projects:

$$C_P = [(\omega \cdot L + I)_P \cdot (1 - sr_P)] \cdot i_P \qquad (1)$$

With $\omega$ denoting R&D employees' wages, $L$ denotes the number of R&D employees, $I$ other physical investments and $P$ can denote research ($P = R$) or development projects ($P = D$). Firms need to finance the project costs either internally or externally and face an internal cost of capital or an interest rate of $i$. The de-facto project costs will also depend on the presence of public R&D grants, more precisely on the subsidy rate $sr$ with $0 < sr < 1$.

Based on the above and in line with the existing literature, we expect to find positive *direct effects*, both for research grants on research investment and for development grants on development investment. These effects materialize at the project-level during the duration of the co-funded project and therefore qualify as contemporaneous. From equation (1), we cannot derive expectations regarding the effects of grants beyond the project duration. In principle, it is possible that firms increase their R&D spending, beyond the co-funded project. This may arise if the grant has longer lasting effects on the number R&D employees hired, their longer-run R&D efficiency or the firm's cost of capital, for instance. Here, we focus on the direct effects of the grant on the project-level cost function during the duration of the grant.[1] It should be noted, however, that median grant length is between 23 and 30 months so that both financial constraints alleviation as well as complementarity effects can realistically materialize during this period. Indeed, previous findings have repeatedly shown positive additionality of R&D grants on R&D spending in Flanders (see e.g., Aerts and Schmidt 2008; Czarnitzki and Lopes-Bento 2013; and Hottenrott and Lopes-Bento 2014) and elsewhere in Europe (Duguet 2004; Czarnitzki and Licht 2006; Görg and Strobl 2007; Czarnitzki et al. 2007; González and Pazó 2008; Carboni 2011; Czarnitzki and Lopes-Bento 2015).

We therefore hypothesize that

*Hypothesis 1a: there are positive direct effects from research grants on research expenditures*

and

*Hypothesis 1b: there are positive direct effects from development grants on development expenditures.*

Similarly, mixed grants should have a positive effect on overall R&D investment.

Due to asymmetric information and uncertainty, research projects are more costly to finance externally, resulting in a higher cost of capital ($i_R > i_D$) thereby rendering these projects more costly overall[2] (Czarnitzki et al. 2011). If research investments are indeed more prone to market failure also in terms of spillovers, research grants that provide compensation may therefore trigger higher additionality than development grants. Development projects that are less prone to such market failures may have been conducted even in the absence of the grant. We therefore hypothesize that

---

[2] Internal cost of capital, i.e. the opportunity cost of investing the research funds in other projects with lower uncertainty, may be higher as well.

*Hypothesis 2: the direct effects are larger for research grants than for development grants.*

In line with the reasoning for research grants, we expect mixed grants, that cover both research and development activities, to have a larger impact at the research stage. Since development activities tend to be less dependent on internal financing than research (Czarnitzki et al. 2011), the cash shock through the grant will translate into increased investment in the latter. We therefore hypothesize that

*Hypothesis 3: mixed grants have a larger effect on research expenditures than on development expenditures.*

### *2.2. Cross scheme additionality*

In addition to direct effects, targeted grants may also generate cross scheme effects. Recipients of research (development) grants may also invest more in development (research) in response to the grant. Such cross scheme effects may be considered as behavioral additionality, reflecting changes in the processes that take place within the firms after receiving support (Clarysse et al. 2009). These effects may arise for several reasons. The first relates to different levels of financing constraints for research versus development projects, as discussed supra. When grant-recipient firms operate with fixed R&D budgets in the short term, they may re-allocate freed resources to those activities for which external funding is more costly to obtain. As the financing costs for research are likely to be higher than for development projects, ceteris paribus, we particularly expect cross effects from development subsidies on research spending. In other words, even if $sr_R$ is zero, we might observe an increase in research spending if $sr_D > 0$[3].

[3] Since the funding agency has relatively little control over the exact use of the money in practice, budget shifts can easily occur. Indeed, in the vast majority of cases, the lion's share of the grant goes into the salary of R&D employees. The agency only observes whether the indicated number of people has been paid, but it cannot observe what they have been working on.

Secondly, research and development are often complementary activities. While cross scheme effects have not been looked at in the R&D literature, possible complementarity between research and development activities has been discussed extensively. Complementarity between both sets of activities results from the notion that research provides a more fundamental understanding of the technology landscape (Rosenberg 1990). As such, research activities will guide development activities in the direction of the most promising technological avenues, thereby avoiding wasteful experimentation (Fleming and Sorenson 2004; Cassiman et al. 2002). In addition, a better and more fundamental understanding of the technology landscape leads to a better identification, absorption, and integration of external knowledge (Cohen and Levinthal 1989; Gambardella 1995; Cockburn and Henderson 1998; Cassiman and Veugelers 2006), in turn, leading to increased productivity of the development process (Fabrizio 2009; Cassiman et al. 2008). Likewise, development may result in new insights that inform ongoing research projects and improve targeting basic research efforts.

The expected rate of return of engaging in research or development thus depends on the combined outcome of research and development projects. In other words, investment into one of these activities will have an impact on the returns to the other activity. This implies that subsidizing one activity will affect the incentives to engage in the other activity as well, thereby resulting in cross scheme effects.

A very simple model based on Cassiman et al. (2002) serves to illustrate the cross scheme effects arising from complementarity. The effective knowledge base of a firm, $X$, used to generate new products or processes, is modeled as:

$$X = D^a(1 + R)^b \qquad (2)$$

Development is specific to a firm's business and, hence, necessary to build an effective knowledge base. Although a firm can obtain an effective knowledge base without investing in research, investing in research will serve to improve the efficiency of development. The parameters *a* and *b,* where $a + b < 1$, are measures of the efficiency of development and research investments, respectively.

The effective knowledge base *X* drives the firm's revenues $B = f(X)$. We assume a simple linear relationship $B=MX$ where *M* represents the size of the market for the innovation, the willingness to pay and the extent to which the firm can appropriate its share of the market. Using (1) to describe the costs of the investment projects, we can express the firm's choice to engage in research and development activities in the presence of public grants in order to maximize its profits *V* as follows:

$$\max_{R,D} V = (MD^a(1+R)^b) - (i_D D(1 - sr_D) + i_R R(1 - sr_R)) \tag{3}$$

Complementarity implies that a higher level of research (development) investments will lead to higher returns to development (research) investments. Technically, complementarity is present if $\frac{\partial^2 V}{\partial D \partial R} > 0$. Thus, a firm that engages in research activities will be more likely to invest also in product or process development, as these activities have a higher return when combined with research. Vice versa, development activities increase incentives to engage in research that supports these development investments.

It can be easily checked that because of (2), solving (3) leads indeed to $\frac{\partial^2 V}{\partial D \partial R} > 0$.[4] Given the complementarity between research and development, solving expression (3) shows that research grants will have a positive effect on the firm's optimal development investments since $\frac{\partial D^*}{\partial sr_R} > 0$[5] and similarly development grants will have a positive effect on a firm's optimal research investments since $\frac{\partial R^*}{\partial sr_D} > 0$.

[4] As the first order condition for D is $aMD^{a-1}(1+R)^b - (1 - sr_R)$, we get $\frac{\partial^2 V}{\partial D \partial R} = abMD^{a-1}(1+R)^{b-1} > 0$.

[5] As we have $D^* = [(1 - sr_d)^{b-1}(1 - sr_r)^{-b} a^{1-b} b^b M]^{\frac{1}{1-a-b}}$, we get $\frac{\partial D^*}{\partial sr_R} = \frac{b}{(1-a-b)} D^*(1 - sr_R)^{-1} > 0$.

Thus, complementarity between research and development will induce firms to increase their investment in development if they received a grant for research and vice versa. We can therefore expect that:

*Hypothesis 4a: there are positive cross scheme effects from research grants on development spending.*

*Hypothesis 4b: there are positive cross scheme effects from development grants on research spending.*

However, these cross effects do not need to be symmetric, as they depend on the efficiency of the firm in increasing their research (development) knowledge base from increased spending, i.e. different values for $a$ and $b$ in (2). For instance, when firms are more efficient in development than in research, the cross effects from research grants on development spending may be higher than then cross effect from development grants on research spending and vice versa.

### 2.3 The Flemish R and D policy

Flanders, like many industrialized economies, has programs in place for subsidizing R&D projects in the private sector. The Flemish funding agency (IWT), an independent government body, administers the permanently open and non-thematic R&D subsidy scheme. Any firm located in Flanders may submit a project proposal in any technological field at any time of the year. Unlike the case of public “top-down R&D programs” such as thematic calls for project proposals issued by the government or public procurement, for IWT subsidies, the project idea and the planning is initiated by the applying company and not by the government itself. The program is therefore characterized by a bottom-up approach, which leaves the project choice and timing to the applicant. Once the project is submitted, an external board of referees evaluates the applications and decides whether the project is eligible for funding based on a set of criteria including novelty, feasibility and valorization potential. Upon approval, the funding agency transfers the first 20% of the approved amount to the company. Additional 20% are released on an annual or bi-annual basis and the final amount is transferred at the end of the last year, based on a final report by the company to the funding agency. From 1997 to 2011, the Flemish government co-funded a total number of 4,115 projects in 2,187 different firms.[6] As can be seen in Figure 1, an increasing number of firms participated in the Flemish subsidy scheme over the considered period. While the average size of the government's contribution per project remained rather constant over time, the overall number of co-funded projects and the total amount of funding doubled.

Over the past decade, the Flemish funding agency moved its policy focus toward distinct grants for research next to development projects. These targeted schemes differ not only in terms of the projects' foci, but also with respect to the share in total project costs borne by the funding agency. The share of costs covered by the government, i.e. the subsidy rate, varies for industrial 'basic and strategic' research, 'experimental development and prototyping,' and so-called 'mixed projects.' For research projects, the base rate covers up to 50% of the project costs and for development projects up to 25%. Mixed projects are in between the two.[7] In both schemes, an additional 10% may be granted to medium-sized firms and an extra 20% to small firms. Collaborative projects may receive another additional 10% if the collaboration takes place at an international level or jointly with a small firm. The minimum project size is €100,000 and the grant amount is capped at €3 million per project.[8] Figure 2 shows that until the early 2000s, mixed projects accounted for the lion's share among all grants. By 2005, mixed projects

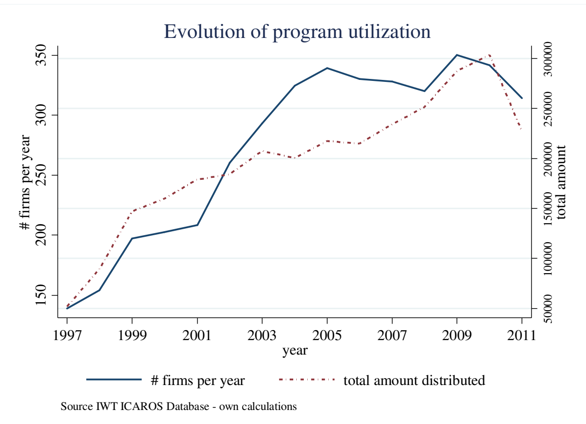
[6] Direct grants are not the only R&D policy instrument in Flanders. While they account for the lion's share of the R&D support for firms in Flanders, there are also tax credits in place from the federal Belgian government. The most prominent one is designed as a partial wage withholding tax exemption on researchers' wages. In addition to that, but used to a much lesser extent, tax benefits on patent income (an 80% tax exemption) and a 13.5% one-shot or 20.5% spread investment deduction also exist at the federal level. In 2011, for instance, a surprisingly low number of firms, a mere 159 firms, used the investment deduction and 212 firms made use of the patent income deduction in Belgium (Dumont 2015, Table 1). We discuss the implications for the coexistence of other policy instruments for our analysis in section 6.

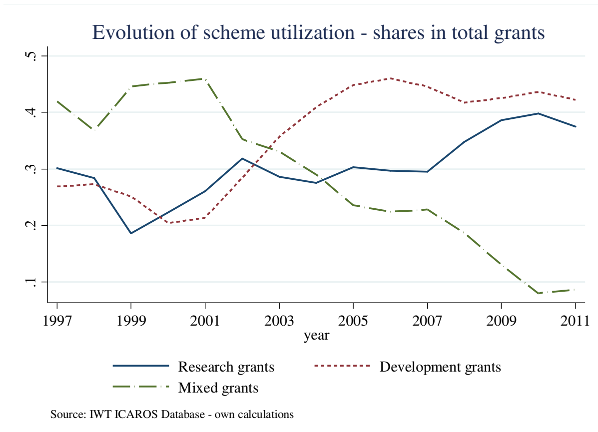
[7] See Figure A.1 in the Appendix for kernel density estimates of the distribution of subsidy rates per scheme.

[8] See http://www.iwt.be/english/funding/subsidy/industrial-projects.

had been overtaken by pure development grants and by pure research grants in terms of their share in total granted projects, reflecting the shifting focus of the agency towards targeted schemes.

Table 1 summarizes the key characteristics of the subsidy schemes for the period 1997–2011. The amounts refer to the government's share in total project costs. Among the subsidized firms the median number of subsidized projects per firm during the entire period is four (average = 13.7) and the average payment received is €259,000 (median = 111). Average amounts are highest for mixed projects and lowest for research grants, on average. However, there is substantial variation within schemes and the standard deviation is higher for research grants compared to development grants. In terms of project duration, the average project length is two years. The mean is lower for research projects and higher for mixed projects, and duration variance is highest for research projects ranging from one to 60 months. The average number of partners in joint projects does not differ substantially across schemes with a mean number of 1.5 partners for research and approximately 1.4 for development projects. For mixed-scheme projects, the mean is slightly higher with an average of 1.9 partners.




**Figures 1 and 2: Evolution of participation in the subsidy program and grants by type of scheme (amounts in T Euros)**

**Table 1: Co-financed R&D projects in the Flemish innovation policy design 1997–2011**

| | *mean* | *median* | *std. dev.* | *min* | *max* |
|---|---|---|---|---|---|
| Projects per firm (entire period) | 13.73 | 4 | 27.01 | 1 | 146 |
| Partners per project | 1.56 | 1 | 1.27 | 1 | 13 |
| Duration Research (in months)* | 18.38 | 12 | 12.45 | 1 | 60 |
| Duration Development (in months)** | 21.60 | 23 | 8.02 | 3 | 52 |
| Duration Mixed (in months)*** | 29.50 | 30 | 7.48 | 6 | 48 |
| Project duration overall (in months) | 23.38 | 24 | 11.28 | 1 | 63 |
| Av. subsidy rate (fraction of total cost) | 0.46 | 0.45 | 0.142 | 0.079 | 1 |
| Research grant (amt. in T€)* | 179.07 | 26.23 | 449.59 | 0.15 | 4,981.58 |
| Development grant (amt. in T€)** | 220.01 | 107.06 | 338.05 | 0.945 | 4,896.84 |
| Mixed grant (amt. in T€)*** | 283.50 | 457.26 | 541.20 | 4.48 | 4,302.33 |
| Av. subsidy size (amt. in T€) | 258.85 | 111.38 | 441.88 | 0.15 | 4,981.59 |

Note: Calculations based on IWT ICAROS database. *3,791 obs., **4,511 obs., ***3,049 obs. Amounts are calculated per partner and project.

# 3. Empirical strategy

We estimate the direct average treatment effects and the cross scheme average treatment effects using a nearest-neighbor propensity score matching procedure. As a robustness test, we present a set of instrumental variables regressions taking into account potential selection on *un*observable factors (see section 4.2 and Appendix 3 for details).

*Treatment effects estimation*

The average treatment effect on the treated is estimated by an econometric matching estimator which addresses the question of "How much would a treated firm have invested in R&D for the duration of an R&D project (or research or development project) if it had not received a public grant?" Given that the counterfactual situation is not observable, it has to be approximated through estimation. In order for this approximation to reveal the theorized effects, we compare the outcome variable of treated and non-treated firms for the duration of the co-funded R&D (or research or development) project. In order to do so, we perform a nearest neighbor propensity score matching. That is, we pair each subsidy recipient with a non-recipient firm by choosing the nearest "twin" based on their similarity in the estimated probability of receiving a certain type of grant. This setting allows us to take into account that (the different types of)

grants are not randomly distributed but are subject to selection. The matching estimator accounts for this selection on observables when looking for the single most similar firm in terms of grant probability, i.e. the propensity score. The estimated probabilities stem from a probit estimation for the case of any type of grant *($S_{rd}$)*. Since a firm that receives one type of grant may also be more likely to receive another type of grant compared to a firm that has not received a grant, the probabilities for specific grant types stem from a multinomial probit estimation for the receipt of a research grant *($S_r$)*, a development grant *($S_d$)* and a mixed grant *($S_{mix}$)*. The multinomial probit estimation takes the correlations between the three equations into account. Firms that receive multiple grants from different schemes in the same year are considered under a separate treatment definition *($S_{mult}$)* for which we estimate a single-equation probit model.
In these estimations, we control for any observable characteristics likely to drive the selection into the respective funding schemes. After having paired each treated firm with the most similar non-treated firm, any remaining differences are attributed to the policy effect. In addition to the similarity in the propensity score, we use elements of exact matching (EM) by requiring that selected control firms belong to the same industry and are observed in the same year as the firms in the treatment group.[9] A caliper is further used to restrict the distance between the treated firm and its control in order to avoid bad matches that could bias the estimates. Furthermore, since particularly the level of development investments is typically higher in larger firms (Arrow 1993) – which is also the case in our sample – we use an SME dummy as an additional exact matching criterion for development grants. This requires subsidized SMEs to only be matched to non-subsidized SMEs for these funding schemes, thereby ensuring the quality of the matching estimation.

In order for the matching estimator to be valid, the conditional independence assumption (CIA) has to hold (Rubin 1977). In other words, to overcome the selection problem,

[9] For the detailed matching protocol, see Table A.1 in Appendix 1.

participation and potential outcome have to be independent for individuals with the same set of exogenous characteristics *X*. Thus, the critical assumption using the matching approach is to observe all relevant factors that determine selection into the subsidy program. If this assumption holds, the average treatment effect (ATT) on the treated firms can be represented as follows:

$$\alpha^{TT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(Y_i^T - \hat{Y}_i^c\right) \tag{4}$$

where $Y_i^T$ indicates the outcome of treated firms under treatment T (T∈ {R&D, R, D, mix, mult}) and $\hat{Y}_i^c$ the counterfactual situation, i.e., the potential outcome which would have been realized if the treatment group had not been treated. Note that $N^T$ refers to number of firms in a specific treatment definition.

Given that we have multiple treatments, we estimate several different treatment effects. More precisely, we distinguish the following nine effects:

(i) the effect from any subsidy received on overall R&D expenditures (this treatment comprises all subsidy types: mixed, research and development grants):

$$\alpha^{TT\_S_{rd}\_R\&D} = \frac{1}{N^{T\_R\&D}} \sum_{i=1}^{N^T}(Y_i^{R\&D} - \widehat{Y_i^C}), \tag{5}$$

(ii) the *direct* effect of a research grant on research expenditures:

$$\alpha^{TT\_S_r\_R} = \frac{1}{N^{T\_R}} \sum_{i=1}^{N^T}(Y_i^R - \widehat{Y_i^C}), \tag{6}$$

(iii) the *direct* effect of a development grant on development expenditures:

$$\alpha^{TT\_S_d\_D} = \frac{1}{N^{T\_D}} \sum_{i=1}^{N^T}( Y_i^D - \widehat{Y_i^C}), \tag{7}$$

(iv) the *cross* effect of a research grant on development expenditures:

$$\alpha^{TT\_S_r\_D} = \frac{1}{N^{T\_R}} \sum_{i=1}^{N^T}(Y_i^R - \widehat{Y_i^C}), \tag{8}$$

(v) the *cross* effect of a development grant on research expenditures:

$$\alpha^{TT\_S_D\_R} = \frac{1}{N^{T\_D}} \sum_{i=1}^{N^T}(Y_i^D - \widehat{Y_i^C}). \tag{9}$$

In order to compare the ATT's from these the targeted schemes with the ATTs of the mixed grant schemes, we also estimate three different treatment effects for mixed grants:

(vi) the effect of a mixed grant on overall R&D expenditures:

$$\alpha^{TT\_S_{mix}\_R\&D} = \frac{1}{N^{T\_mix}} \sum_{i=1}^{N^T} (Y_i^{mix} - \widehat{Y_i^C}), \tag{10}$$

(vii) the effect of a mixed grant on research expenditures:

$$\alpha^{TT\_S_{mix}\_R} = \frac{1}{N^{T\_mix}} \sum_{i=1}^{N^T} (Y_i^{mix} - \widehat{Y_i^C}), \tag{11}$$

(viii) the effect of a mixed grant on development expenditures:

$$\alpha^{TT\_S_{mix}\_D} = \frac{1}{N^{T\_mix}} \sum_{i=1}^{N^T} (Y_i^{mix} - \widehat{Y_i^C}). \tag{12}$$

Importantly, we exclude firms from the treatment groups if they held grants from multiple schemes in the same year to avoid confounding the cross effects. For instance, if a firm held a mixed grant and a research grant in the same year, we consider it as a multiple treatment case for which we define an additional treatment ($S_{mult}$):

(ix) the effect of multiple grants on R&D expenditures:

$$\alpha^{TT\_S_{mult}\_R\&D} = \frac{1}{N^{T\_mult}} \sum_{i=1}^{N^T} (Y_i^{mult} - \widehat{Y_i^C}), \tag{13}$$

It is important to stress that the control group is always exclusively composed of unsubsidized firms. For example, if we consider a firm that has received a research grant, the control group is composed exclusively of firms that did not received any grants (i.e. neither from a regional, nor from a national or an international funding agency).

**Data**

The public funding information was provided by the funding agency IWT and contains detailed information on the duration of the project, the total amount received and the type of subsidy scheme under which the subsidy had been granted. The data on firms' research and development expenditures stem from the Flemish part of the OECD R&D survey. This survey composes the Main Science and Technology Indicators across OECD countries (OECD 1993; OECD/Eurostat 2005). In Flanders, the R&D survey draws from a permanent inventory of all R&D-active firms. The OECD survey asks firms to split their total R&D expenditures into their research and development components. A guideline for respondents on how to attribute activities to research and development is provided with examples and definitions based on the Frascati Manual. Beyond the budgets for R&D, the survey also contains a wealth of information on other firm characteristics that can be used for constructing control variables including the number of R&D employees, group and ownership structure, subsidies from sources outside Flanders, and R&D collaborations.

We match the survey data and the funding information based on the firms' unique VAT numbers. It is an important advantage of our approach that we combine information on R&D expenditures stemming from a different data source with the grant data from the funding agency. This reduces the risk that firms misreported their R&D spending.

The analysis makes use of five consecutive waves of the biannual survey covering the twelve year period from 2000 to 2011 and comprises R&D-active firms from manufacturing and business-related service sectors. We complemented the repeated cross-sectional survey data with patent statistics issued by the European Patent Office (EPO).[10] Finally, we collected the firms' balance sheet information, in particular the firms' tangible assets, from the Belfirst database provided by Bureau van Dijk.

After the elimination of incomplete records, the final sample contains a total number of 12,138 firm-year observations corresponding to 1,994 different firms. About 15% of these firm-

[10] The "EPO/OECD patent citations database" covers all patents applied for at the EPO since its foundation in 1978 as well as all patents applied for under the Patent Cooperation Treaty (PCT) in which the EPO is designated, so-called "Euro-PCT applications." Data from the Belgian patent office serves as information on patents filed only in Belgium. Patent information is available as a time series from 1978 onward and was collected using text field search. We checked all potential hits of the text field search engine manually before merging it with the firm-level survey data.

year observations have benefited from some type of IWT subsidy within the three thematic schemes. Roughly 2.3% of the observations in the survey reported the receipt of an IWT grant other than the ones under review in this study, or a grant from another funding source such as the federal government or the EU during that time.

In terms of the distribution of IWT grants within our sample, we find that while about 7.5% of the firm-year observations benefited from a development grant during the period under review, only 4.4% received a research grant (see Table A.3 in Appendix 2). When exclusively considering firms with grants, we see that 29% of the firms had a research grant as compared to 49% that received a development grant. In terms of grant size, the average annualized amount for a development grant among the recipient firms is close to €81,000 compared to €65,000 for a research grant. As firms may hold multiple grants, the overall annualized amount is approximately €288,000 among the grant recipients.

***Research and Development investments***

The outcome variables in the treatment effect estimations are firms' R&D (as well as research and development) *intensities*, which are the ratios of R&D (respectively R and D) to sales,[11] and the levels of R&D (and R and D) *expenditures*. In line with previous studies, we scale the outcome variables to account for the skewness in the distribution and take natural logarithms (plus one unit) for spending levels. As we have information on the subsidy amounts received, we construct our outcome variables as the *net* amounts. That is, we deduct the annualized amount of the subsidy from the firms' total annual research and development expenditures. We distribute the full amount of the grant on a monthly basis over the duration of the project to

[11] Although intensities reduce the influence of outliers in R&D spending on the estimated average treatment effect, a drawback of the use of intensities is that they vary not only with R&D spending, but also with changes in sales. We still employ these outcome variables for comparability with previous studies using R&D intensities as outcome variables. See, for instance, Czarnitzki and Licht (2006), Czarnitzki et al. (2007), Aerts and Schmidt (2008), Czarnitzki and Lopes-Bento (2013), and Hottenrott and Lopes-Bento (2014), among others.

assign the corresponding grant to the firms' spending during that time. Amounts from the mixed scheme are deducted in equal shares from total research and development expenditures.

***Probability to receive subsidies***

We model the receipt of a grant from any scheme by a dummy variable equal to one if a firm received financial support, zero otherwise *($S_{rd}$)*. When looking at the different types of grants, we disentangle the receipt of a research project grant ($S_r$), a development project grant ($S_d$), and a mixed-scheme project grant *($S_{mix}$)*. Firms with grants from more than one scheme in the same year are considered as a separate treatment ($S_{mult}$)[12].

Since important determinants of grant receipt are familiarity with the subsidy program and earlier successful applications, we account for experience within the subsidy scheme. Firms may also switch between schemes over time. That is, they receive grants from different schemes in consecutive years. For instance, firms can obtain a development grant after they already received a research grant in earlier years. In the estimation of the propensity score we therefore account for past grant success also across schemes. In particular, we include separate indicator variables for past subsidy receipt for all three schemes into each model (*Past research grants, Past development grants, Past mixed grants*).

We control for other characteristics likely to influence the receipt of either one of the policy treatments. The number of employees takes into account possible size effects. Given that this variable is skewed, it enters the model as a natural logarithm [*ln(employees)*]. We also allow for a potential non-linear relationship by including its squared value. *Labour productivity* is measured as sales per employee (in T€). We further include a dummy variable that is equal to one if a firm qualifies as an SME (*SME*). Belgian SMEs are eligible for a higher subsidy rate

[12] The multiple grant cases include 58 case of combined `R' and `D' grants, 94 cases of `R' and mixed grants, 101 cases of `D' and mixed and 41 cases of firms that held an `R', a `D' and mixed grant in the same year. These cases are excluded from the treatment variables capturing the distinct schemes.

than large-size firms, which may impact the likelihood of applying for, and hence receiving a subsidy.[13] The log of the firm's age [*ln(age)*] is included in the analysis as older firms may have more experience than younger firms, thus reducing their application costs. On the other hand, young firms are more likely to be financially constrained than older or more established firms are, and might therefore be more likely to apply for public support. Similarly to size, we allow for a non-linear relationship by including $ln(age)^2$.

Moreover, we account for whether a firm collaborated on R&D activities (*R&D cooperation*). Given that the Belgian funding agency encourages firms to collaborate in their R&D activities, being a collaborator may be an important determinant of applying for and receipt of public support.

In addition, we include a dummy variable capturing whether or not a firm is part of an enterprise group with a foreign parent company (*foreign group*). It is a priori not clear whether belonging to a group with a foreign parent has a positive or negative influence on the receipt of a subsidy by the Flemish funding agency. Firms that belong to a group with a parent located in a different country may be less likely to apply for a subsidy in Belgium than other firms. In addition, firms that have a large majority shareholder do not qualify for the Belgian SME programs in which higher subsidy rates are attributed to recipient firms, giving them fewer incentives to apply. On the other hand, firms with a foreign parent company might be more likely to collaborate internationally and be better able to incur the application costs.

R&D experience, especially if successful, may increase a firm's likelihood of applying again and of being granted a public subsidy. To capture these dynamics, we include the firms' past patent stock in our regression. Patent stocks *(PS)* are computed as a time series of patent applications with a 15% rate of obsolescence of knowledge capital, as it is common in the literature (see e.g., Griliches and Mairesse 1984; Jaffe 1986):

[13] SME follows the definition of the European Commission, according to which an SME should have less than 250 employees and have sales less than €50 million (or a balance sheet total of less than €43 million).

$$PS_{i,t} = (1 - \delta)PS_{i,t-1} + PATAPPL_{i,t}$$

where *PATAPPL* is the number of patent applications in each year. The patent stock enters into the regression as patent stock per employee to avoid potential multicollinearity with firm size.

We further include firms' capital intensity in order to control for differences in the technologies used in the production process. Finally, 16 industry dummies control for unobserved heterogeneity and technological opportunity or appropriation across sectors (see Table A.2 of Appendix 2 for the distribution of firms across industries). Time dummies (years) are included to capture macroeconomic shocks and changes in the policy design or implementation over years.

***Descriptive statistics***

Table 2a shows descriptive statistics for the outcome variables of interest distinguishing between subsidized and non-subsidized firms. The latter serve as control groups in our empirical analysis as these firms did not receive any grants, either from the Flemish funding agency or from any other funding source like, for instance, the national government or the European Union.[14]

Subsidized firms, no matter what type of support they receive, have on average a higher net R&D intensity as well as for both stages of R&D: research intensity as well as development intensity. Firms that received multiple grants from different schemes during the same year, show the highest R&D intensities.[15]

Comparing research grant and development grant recipients (III vs IV in Table 2b) shows that the research grant-receivers have larger development intensities, while development

[14] The information on funding sources other than IWT is obtained from the survey. Firms are explicitly asked to indicate regional, national, and supranational funding sources for supported R&D projects.

[15] While the overall and within year correlations between research and development expenditures are not that extraordinary high in absolute terms (varying whether we look at intensities [0.21], logs [0.38] or levels [0.46]), they are statistically significant. This points to the underlying complementarity between the two activities and stresses the need for investigating both research and development expenditures as well as R&D as outcome variables.

grant-receiving firms do not differ in research intensity from research-grant recipients. This could already be reminiscent of the complementary role research plays with regard to increasing the incentives for development activities.

With respect to the control variables (reported in Table A.4a in Appendix 2), on average, subsidized firms are larger compared to non-subsidized firms. This is particularly true for firms with mixed and multiple grants. Likewise, subsidized firms – no matter what type of scheme – have significantly higher patent stocks per employee and have received subsidies more often in previous years. Furthermore, we see that firms with multiple grants have on average more experience with the all three schemes. Subsidized firms (again irrespective of the scheme) further engage significantly more often in R&D collaboration and they are on average younger (especially research grant recipients) than non-grant recipients. In terms of ownership characteristics little differences exist between the groups except that mixed and multiple grant holder are more often foreign owned.

**Table 2a: Descriptive statistics by group of the outcome variables**

| | I<br>No grants<br>Control group<br>N = 10,281 | | II<br>Any grant[§]<br>$S_{rd}$<br>N = 1,563 | | III<br>Research grant<br>$S_r$<br>N = 336 | | IV<br>Develop. grant<br>$S_d$<br>N = 705 | | V<br>Mixed grant<br>$S_{mix}$<br>N = 522 | | VI<br>Multiple grants<br>$S_{mult}$<br>N = 294 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Outcome variables** | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. |
| *Net R&D intensity* | 0.062 | 0.165 | 0.131 | 0.233 | 0.162 | 0.252 | 0.120 | 0.229 | 0.125 | 0.222 | 0.186 | 0.275 |
| *Net Development intensity* | 0.034 | 0.108 | 0.056 | 0.133 | 0.082 | 0.165 | 0.045 | 0.124 | 0.054 | 0.118 | 0.082 | 0.159 |
| *Net Research intensity* | 0.028 | 0.103 | 0.075 | 0.173 | 0.081 | 0.163 | 0.075 | 0.175 | 0.072 | 0.176 | 0.104 | 0.185 |
| *ln(Net R&D)* | 3.766 | 2.822 | 5.743 | 2.448 | 5.451 | 2.413 | 5.195 | 2.286 | 6.672 | 2.416 | 7.952 | 2.705 |
| *ln(Net Development)* | 2.951 | 2.691 | 4.132 | 3.144 | 4.210 | 2.778 | 3.272 | 2.957 | 5.243 | 3.257 | 6.443 | 3.568 |
| *ln(Net Research)* | 2.545 | 2.670 | 4.431 | 2.831 | 3.840 | 3.039 | 4.208 | 2.530 | 5.112 | 2.947 | 6.688 | 3.183 |

Notes: [§]contains firms with mixed grants only, research grants only and developments grants only, i.e. excludes multiple grants from different schemes. N refers to the number of firm-year observations.

**Table 2b: T-test on mean difference of the outcome variables**

| | **I vs II** | **I vs III** | **I vs IV** | **I vs V** | **l vs VI** | **III vs IV** | **III vs VI** | **IV vs VI** | **V vs VI** |
|---|---|---|---|---|---|---|---|---|---|
| | **P-values of two-sided t-tests on mean differences of the groups of interest (Pr(\|T\| > \|t\|))** | | | | | | | | |
| *Net R&D intensity* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.007 | 0.261 | 0.000 | 0.001 |
| *Net Dev. Intensity* | 0.000 | 0.000 | 0.009 | 0.000 | 0.000 | 0.000 | 0.988 | 0.000 | 0.004 |
| *Net Research intensity* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.605 | 0.092 | 0.018 | 0.013 |
| *ln(Net R&D )* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.098 | 0.000 | 0.000 | 0.000 |
| *ln(Net development )* | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *ln(Net research)* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.040 | 0.000 | 0.000 | 0.000 |

# 4. Estimation results

## 4.1. The matching results

Table 3 shows the results of the probit estimations on the likelihood of receiving a grant. The first model predicts the probability of the receipt of any type of subsidy, ignoring the distinction between research grants, development grants and mixed grants. The second model estimates probabilities of receiving a research, a development or a mixed grant. The third model estimates the probability of holding grants from multiple schemes in the same year. The predicted probabilities serve as the basis for the propensity score matching.

**Table 3: Probit estimations on probability of receiving any grant or multiple grants; multinomial probit estimation on the probability of receiving a research, a development or a mixed grant (exclusive groups)**

| | Model 1 | Model 2 | | | Model 3 |
|---|---|---|---|---|---|
| | *Probit estimation* | *Multinomial probit estimation* | | | *Probit estimation* |
| | $S_{rd}$ | $S_r$ | $S_d$ | $S_{mix}$ | $S_{mult}$ |
| | **N=11,844**[§] | **N=11,844** | | | **N=10,575** |
| | dy/dx | dy/dx | dy/dx | dy/dx | dy/dx |
| *R&D cooperation* | 0.139*** | 0.030*** | 0.053*** | 0.053*** | 0.025*** |
| | (0.007) | (0.004) | (0.005) | (0.004) | (0.003) |
| *Patent stock per employee* | 0.172*** | 0.032*** | 0.078*** | 0.055*** | 0.027*** |
| | (0.023) | (0.010) | (0.015) | (0.011) | (0.006) |
| *Labor productivity* | <-0.001*** | <-0.001*** | <-0.001** | <0.001 | <-0.001*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| *Past research grants* | 0.116*** | 0.040*** | 0.042*** | 0.024*** | 0.027*** |
| | (0.012) | (0.005) | (0.008) | (0.007) | (0.004) |
| *Past development grants* | 0.102*** | 0.019*** | 0.079*** | -0.008 | 0.032*** |
| | (0.011) | (0.005) | (0.007) | (0.007) | (0.003) |
| *Past mixed grants* | 0.159*** | 0.029*** | 0.044*** | 0.071*** | 0.042*** |
| | (0.012) | (0.006) | (0.009) | (0.006) | (0.003) |
| *Foreign group* | -0.004 | -0.003 | -0.018*** | 0.015*** | -0.003 |
| | (0.008) | (0.004) | (0.006) | (0.004) | (0.003) |
| *SME* | -0.020 | 0.002 | -0.010 | -0.013** | 0.006 |
| | (0.012) | (0.007) | (0.010) | (0.007) | (0.004) |
| *ln(Employees)* | 0.009*** | 0.000 | -0.001 | 0.010*** | 0.008*** |
| | (0.003) | (0.001) | (0.002) | (0.002) | (0.001) |
| *ln(Capital intensity)* | 0.001 | 0.002 | 0.001 | -0.002 | 0.001 |
| | (0.003) | (0.001) | (0.002) | (0.002) | (0.001) |
| *ln(Age)* | -0.032*** | -0.009*** | -0.011*** | -0.013*** | -0.008*** |

| | | | | | |
|---|---|---|---|---|---|
| | (0.005) | (0.003) | (0.004) | (0.003) | (0.002) |
| Overall model significance | LR chi$^2$(39) = 1,535.79*** | Wald chi$^2$(117) = 1,787.43*** | | | LR chi$^2$(33) = 1,390.02*** |
| Joint significance of industry dummies | chi$^2$(15) = 87.54*** | chi$^2$( 15) = 25.02** | chi$^2$( 15) = 78.74*** | chi$^2$( 15) = 44.17*** | chi$^2$( 15) = 35.34*** |
| Joint significance of time dummies | chi$^2$(11) = 34.13*** | chi$^2$( 11) = 35.81*** | chi$^2$( 11) = 34.85*** | chi$^2$( 11) = 99.87*** | chi$^2$(11) = 7.52 |

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Average marginal effects reported; standard errors in parentheses. All models contain a constant, industry and year dummies (not presented) and for the second order term of *ln(Age)* no marginal effect is reported. $S_{rd}$ includes research subsidies, development subsidies and mixed grants. N denotes firm-year observations. [§]Number of observations excludes the "pure treatments".

As can be seen from Table 3, past research, development, and mixed grants significantly determine the current grant receipts for current research and development grants. Mixed-grant receipt is more likely when the firm had a research grant in the past. The marginal effect of receiving a development grant after having had a research grant is larger than the probability of receiving a research grant after having had development grant previously. The patent stock per employee as well as R&D collaboration have a positive and significant impact on all grant receipts. Older firms are less likely to receive grants, irrespective of the type of scheme. While being part of a foreign group has a negative impact on receiving a development subsidy, it has a positive impact on receiving a mixed-scheme subsidy. Finally, larger firms are more likely to obtain mixed grants and are also more likely to hold multiple grants from different schemes in the same year. Year and industry dummies are jointly significant pointing to cyclical and industry-specific effects captured by these variables.

Table 4 presents the results from the matching estimation. When looking at any subsidy type, we find positive additionality on all outcome variables of interest. This positive additionality from R&D grants on R&D confirms previous findings. It should be noted that these effects refer to the difference between R&D of the treated and the control firm in the period of the grant receipt. That is, during the annualized duration of the project, recipient firms spend on average more than they would have in absence of public co-funding as approximated by the R&D spending of non-recipient firms. It is reassuring to see that even though previous estimations were based mainly on gross amounts, we find similar results when using the net amounts. These results complement previous findings that rejected a total crowding out by also rejecting partial crowding out.

More interestingly, the results add to previous insights by showing that the additionality is larger for research expenditures than for development for both intensities and for logged levels. When looking at research grants, we see a significant direct effect on research expenditures (Hypothesis 1a) as well as a significant cross effect on development expenditures (Hypothesis 4a). Direct and cross effects from research grants are of similar size, ($Pr(|T| > |t|) = 0.821$ for intensities and $Pr(|T| > |t|) = 0.175$ for the logged level). For development grants, on the other hand, we find no significant direct effect. The evidence therefore does not support Hypothesis 1b, but confirms that research additionality is larger than development additionality (Hypothesis 2). However, there is a positive, significant and relatively large cross effect from development grants to research expenditures (Hypothesis 4b). It is this cross effect that explains the overall positive additionality from development grants on R&D intensity. When looking at the effect of the mixed-scheme grants we find a significant and positive treatment effect on overall R&D expenditures, irrespective of whether we consider intensities or logged levels. This overall effect on R&D intensity is mainly driven by additionality on research intensity, confirming Hypothesis 3. For development expenditures, we find a significant impact of mixed grants on the level of development spending, but an insignificant effect on development intensity, indicating that the additional development expenditures induced by the mixed grant are proportional to sales. For multiple grant holders, treatment effects are overall larger, but again the additionally is observed mostly for research activities.

**Table 4: Matching results**[16]

| Treatment Effects on Outcome Variables | | | | | | |
|---|---|---|---|---|---|---|
| | *Net R&D intensity* | *Net Research intensity* | *Net Development intensity* | *ln(net R&D)* | *ln(net research)* | *ln(net development)* |
| **Treatment** | | | | | | |
| $S_{rd}$ (N=1,438) | 0.041*** | 0.033*** | 0.008* | 1.077*** | 1.062*** | 0.474*** |
| $S_r$ (N=306) | 0.049*** | 0.025** | 0.025** | 0.995*** | 0.488** | 0.913*** |
| $S_d$ (N=653) | 0.045*** | 0.042*** | 0.004 | 0.970*** | 1.210*** | -0.030 |
| $S_{mix}$ (N=428) | 0.052*** | 0.046*** | 0.006 | 1.254*** | 1.143*** | 0.725*** |
| $S_{mult}$ (N=123) | 0.099*** | 0.060*** | 0.040* | 1.401*** | 1.366*** | 0.967** |

Notes: All outcome variables are based on expenditures *net* of the subsidy amount, n indicates the number of matched pairs. *** (**, *) indicate a significance level of 1% (5%, 10%). Only outcome variables are presented. All control variables are balanced after the matching, meaning that no significant mean differences remained. N denotes firm-year observations, i.e. matched pairs. The number of matched pairs per treatment is lower than the number of cases as presented in Table 3 because of observation dropped due to lack of common support or no appropriate match.

As Figure 2 illustrates, there has been a shift in the policy from supporting mixed projects toward targeted research and development support. If the trend toward targeted schemes is indeed beneficial, we should see that the impact of the program overall, that is for *any* treatment ($S_{rd}$)[17] on R&D spending increases over time as the focus shifted toward more targeted grants after 2005. To test this, we regress the estimated treatment effects $\alpha_i{}^{TT}$ at the firm level on a time trend as well as on time dummies. We derive the individual firm additionality as:

$$\alpha_i^{TT*} = Y_i - \hat{Y}_i^c \tag{14}$$

That is, the individual treatment effect is simply the deviation of the treated firms' net expenditures on R&D, research or development from those of its matched twin firm. As shown in Table 5, the time trend is significant and more pronounced for research spending than for development. This confirms earlier insights stressing that the direct effects from research grants

[16] As shown by the overall insignificance of the probits after the matching, the matching was balanced in all cases.

[17] Note that this is based on the matching estimation. Consequently, the treatment definition excludes firm-year observations for cases in which a firm held grants from multiple schemes.

as well as cross effects from development grants on research spending are mostly responsible for additionality effects.

When replacing the overall time trend with individual time dummies, we see that time dummies are positive and significant as of 2006, pointing to the fact that the additionality is larger when the focused schemes started to dominate. It should be noted that in addition to excluding cases with multiple grants from different schemes, we also control for the number of subsidized projects a firm has within the *same* scheme in one period. This avoids that magnitude of the individual treatment effect is driven by higher amounts of funding through multiple grants. The variable *# of projects* is indeed positive and significant pointing to possible dose effects.

**Table 5: Firm level additionality (from any type of subsidy) over time (N = 1,438)**

| | $\alpha_i^{TT^*}\ln(R\&D_i)$ | $\alpha_i^{TT^*}\ln(Research_i)$ | $\alpha_i^{TT^*}\ln(Develop_i)$ | $\alpha_i^{TT^*}\ln(R\&D_i)$ | $\alpha_i^{TT^*}\ln(Research_i)$ | $\alpha_i^{TT^*}\ln(Develop_i)$ |
|---|---|---|---|---|---|---|
| *Year trend* | 0.154*** | 0.182*** | 0.085** | | | |
| | (0.033) | (0.036) | (0.038) | | | |
| *# of* | 0.870*** | 0.758** | 1. 041*** | 0.877*** | 0.786*** | 1.030*** |
| | (0.220) | (0.271) | (0.265) | (0.218) | (0.269) | (0.262) |
| *year 2001* | | | | 0.684* | 0.238 | 0.821** |
| | | | | (0.371) | (0.411) | (0.407) |
| *2002* | | | | -0.384 | -0.095 | -0.327 |
| | | | | (0.400) | (0.458) | (0.455) |
| *2003* | | | | -0.235 | 0.040 | -0.305 |
| | | | | (0.405) | (0.457) | (0.446) |
| *2004* | | | | 0.616 | 0.114 | 0.301 |
| | | | | (0.405) | (0.452) | (0.478) |
| *2005* | | | | 0.407 | 0.239 | 0.031 |
| | | | | (0.428) | (0.447) | (0.493) |
| *2006* | | | | 1.023* | 1.359*** | 0.170 |
| | | | | (0.395) | (0.419) | (0.461) |
| *2007* | | | | 0.972** | 1.036** | 0.896* |
| | | | | (0.431) | (0.454) | (0.477) |
| *2008* | | | | 0.893** | 1.128** | 0.149 |
| | | | | (0.428) | (0.463) | (0.505) |
| *2009* | | | | 1.394*** | 1.472*** | 0.672 |
| | | | | (0.431) | (0.480) | (0.494) |
| *2010* | | | | 1.025** | 0.850* | 0.768 |
| | | | | (0.473) | (0.510) | (0.483) |
| *2011* | | | | 2.193*** | 3.118*** | 1.676** |
| | | | | (0.776) | (0.785) | (0.483) |
| *Constant* | -309.288*** | -363.891*** | -172.065** | -0.551 | -0.503 | -1.007 |
| | (66.199) | (71.291) | (76.851) | (0.394) | (0.455) | (0.459) |
| F-test | 19.23*** | 16.55*** | 9.79*** | 5.69*** | 4.42*** | 3.83*** |

Note: *** (**, *) indicate a significance level of 1% (5%, 10%). Robust standard errors in parenthesis. All treatment effects are based in net amounts. N refers to firm-year observations.

## 4.2 Robustness to matching on observables

Given that the funding agency's selection of R&D grant recipients is likely to be based on observable characteristics, the matching estimator that controls for the selection on observables appears as a suitable tool for impact analysis. While we observe a relatively large number of firm characteristics, we do not claim completeness. Management or project-level information is unavailable to us while it might have been part of the funding agency's decision rule. Moreover, firms also self-select into the application process on such characteristic. We therefore test whether the main conclusions hold once we account for a potential selection on unobservables. In order to do so, we estimate instrumental variable (IV) regressions. The results of the two-stage least squares analysis (2SLS) can be found in Table A.5 in Appendix 3. The instrumental variables pass the commonly applied statistical requirements (see Appendix 3 for more details on the IVs). Yet, they may be disputed from a theoretical point of view. Indeed, finding convincing instruments with the data at hand – and even more so in our case since we need separate instruments for research grants and for development grants -is notoriously difficult. We therefore refrain from interpreting the point estimates individually but use these regressions as a robustness check for the sign and relative magnitude of the main explanatory variables. The results confirm the matching estimation conclusions on the presence of direct as well as cross effects. They also confirm the relative higher direct effect from research grants compared to development grants. In contrast to the matching estimator results, the direct effects in the 2SLS estimations are also significant for development grants. Nevertheless, and in line with the matching results, the coefficients are smallest for the direct effect of development grants.

# 5. Conclusions and discussion

The literature on the effects of R&D subsidies so far provided little insights on differences in the responsiveness of research versus development investments. In addition, possible differences between general R&D subsidy schemes and schemes dedicated to research versus development projects remained unexplored. With higher outgoing spillovers, higher risk and constrained access to external financing, gaps between social and private returns as well as market failures tend be more severe for research than for development projects. Research subsidies may therefore yield higher additionality effects than development subsidies. At the same time, research and development are complementary activities, with one investment increasing the efficiency of the other. Targeted schemes are therefore likely to generate cross-scheme effects, with research grants having knock-on effects on development expenditures and vice versa.

This study contributes to the literature on R&D subsidies by estimating the direct and cross scheme average treatment effects on both research and development investments in recipient firms. Making use of a policy design that explicitly distinguishes between research projects, development projects and mixed R&D projects, matching estimations confirm that, on average, grants increase net R&D spending. The results thus reject total as well as partial crowding out. More importantly, when decomposing the type of grant and the type of investment, the findings show that research grants yield higher average direct effects than development grants. In addition, there are significant cross effects from research grants on development expenditures and from development grants on research expenditures. The results also show that mixed grants, which support both research and development activities, turn out to trigger additional research spending, but not development intensity. Furthermore, as the funding agency gradually moved from mixed schemes towards targeted schemes over time, overall R&D additionality increased.

Our findings are therefore consistent with theory suggesting higher market failures associated with research. The significant cross effects are also consistent with the view that research and development are complementary activities each increasing the productivity of the other. The lower within scheme effectiveness of development grants compared to research grants could be explained by companies shifting their budget from a less financially constrained activity (development) to a more financially constrained activity (research). Alternatively, it could be due to the overall lower average subsidy rate for development in the policy design under review. Based on unreported dose response functions we do not find evidence of higher treatment effects at higher development subsidy rates. Nevertheless, we cannot rule out that if the subsidy rate distribution for development were similar to that of research grants, the average direct additionality may be higher. Either way, the additionality-to-funding amount ratio is higher for research than for development grants, since the mean amount for research grants is lower than for development in the policy scheme under review. Thus, re-directing the amounts spent on development subsidies towards research projects may lead to a better budget utilization of public resources for R&D supporting programs.

These results suggest important policy implications. They recommend a higher priority for subsidy programs targeting research projects. Despite the positive cross effects from development grants on research spending, the average return to funding research projects is higher than the returns to supporting the development stage. Furthermore, funding agencies can expect that their research subsidies will not only invoke additional research with potentially higher social returns, but also additional development activities. All this contrasts with development subsidies, where the direct effects are not obvious. Policy makers can thus expect more bang for the buck for research than for development support.

It should be noted that the existence of tax credits in Belgium does not undermine these conclusions. Since the grants are cost-based, a firm that benefits from a tax exemption on researchers' wages would declare lower costs in a project proposal to the funding agency and hence receive a smaller amount to compensate for the wage expenses of an R&D employee. Consequently, there is little risk that a firm gets the full gross salary in a direct grant and on top of that recovers taxes on that salary. However, we encourage further research on the R&D policy mix to explore the joint use of different policy tools.

Although our results suggest clear policy conclusions, we strongly encourage further research on the efficacy of targeted policy schemes in different environments in order to assess the generalizability of the insights gained in this study. Based on theoretical considerations and empirical findings, our results bear a strong message. We would therefore advise researchers in other countries to investigate whether there are differences in additionality depending on the nature of the (co-) funded project in other institutional contexts as well, as this would allow drawing best practices in innovation policies in a more generalizable way. In addition, we still need a better understanding of the factors explaining the enhanced effect of targeted schemes. These may relate to the strength of the regional innovation eco-systems for research and development and its connectedness. They may also relate to the overall innovation policy in place and the quality of the institutions administering the programs. Moreover, in order to assess the cost-efficiency of targeted schemes, we would need to factor in the administrative cost of providing such targeted programs compared to general ones. Finally, the analysis only looked at the effects for the duration of the grant, which is typically two to three years. Research and development triggered through public co-funding may however affect firms' efforts into research and development well beyond the duration of the supported project and it may affect other dimensions of innovation than expenditures. As stressed by the behavioral additionality literature, the nature of research and development activities may change, for instance, with shifts in openness and collaboration. Since an empirical assessment of the grant–to R&D efficiency relationship is challenging based on firm-level data, future research would gain from being able to zoom in on project or technology-level data of both subsidized and unsubsidized firms.

## References


Aerts, K. and Schmidt, T. (2008), Two for the Price of one? Additionality Effects of R&D Subsidies: A Comparison Between Flanders and Germany, *Research Policy 37*(5), 806–822.

Aghion, P. and Howitt, P. (1998), *Endogenous Growth Theory*. Cambridge, MA. MIT Press.

Akcigit, U., Hanley, D. and Serrano-Velarde, N. (2013), Back to Basics: Basic Research Spillovers, Innovation Policy and Growth, NBER Working Paper No. 19473.

Arrow, K. (1962), *Economic Welfare and the Allocation of Resources for Invention*, in: Nelson, R. R. (Eds.), The Rate and Direction of Inventive Activity, Economic and Social Factors, Princeton, 609-625.

Arrow, K.J. (1993), Innovation in Large and Small Firms, *The Journal of Small Business Finance* 2(2), 111-124.

Carboni, O.A. (2011), R&D Subsidies and Private R&D Expenditures: Evidence from Italian Manufacturing Data, *International Review of Applied Economics 25*(4), 419–439.

Cassiman, B., D. Perez-Castrillo and Veugelers, R. (2002), Endogeneizing Know-How Flows Through the Nature of R&D Investments, *International Journal of Industrial Organisation* 20, 775-799.

Cassiman, B. and Veugelers, R. (2002), R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium, *American Economic Review* 92(4), 1169– 1184.

Cassiman, B. and Veugelers, R. (2006), In Search of Complementarity in Innovation Strategy: Internal R& D and External Knowledge Acquisition, *Management Science* 52(1), 68-82.

Cassiman, B., Veugelers, R. and Zuniga, P. (2008), In Search of Performance Effects of (in)direct Industry Science Links, *Industrial and Corporate Change* 17(4), 611-646.

Clarysse, B., Wright, M., and Mustar, P. (2009). Behavioural additionality of R&D subsidies: A learning perspective, *Research Policy* 38(10), 1517–1533.

Clausen, T.H. (2009), Do Subsidies Have Positive Impacts on R&D and Innovation Activities at the Firm Level?, *Structural Change and Economic Dynamics* 20(4), 239-253.

Cockburn, I. and Henderson, R. (1998), Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery, *Journal of Industrial Economics* 46(2), 157-182.

Cochran, W.G. and Rubin, D.B. (1973), Controlling Bias in Observational Studies: A Review, *The Indian Journal of Statistics* 35, 417-446.

Cohen, W.M. and Leventhal, D.A. (1989), Innovation and Learning: The Two Faces of R&D, *Economic Journal* 99, 569-596.

Czarnitzki, D. and Licht, G. (2006), Additionality of Public R&D Grants in a Transition Economy. *Economics of Transition 14*(1), 101–131.

Czarnitzki, D., Ebersberger, B., and Fier, A. (2007), The Relationship Between R&D Collaboration, Subsidies and R&D Performance: Empirical Evidence from Finland and Germany, *Journal of Applied Econometrics 22*(7), 1347–1366.

Czarnitzki, D., Hottenrott, H. and Thorwarth, S. (2011), Industrial Research versus Development Investment: The Implications of Financial Constraints, *Cambridge Journal of Economics* 35(3), 527-544.

Czarnitzki, D. and Lopes-Bento, C. (2013), Value for Money? New Microeconometric Evidence on Public R&D Grants in Flanders, *Research Policy* 42, 76-89.

Czarnitzki, D. and Lopes-Bento, C. (2015), Innovation subsidies: Does the funding source matter for innovation intensity and performance? Empirical evidence from Germany, Industry and Innovation, 22(2).

David, P. A. and Hall, B. H. (2000), Heart of Darkness: Modeling Public-Private Funding Interactions Inside the R&D Black Box, *Research Policy* 29, 1165-1183.

David, P. A., Hall, B. H., and Toole, A.A. (2000), Is public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence, *Research Policy* 29(4-5), 497–529.

Duguet, E. (2004), Are R&D Subsidies a Substitute or a Complement to Privately Funded R&D?, *Revue D'économie Politique 114*(2), 245–274.

Dumont, M. (2015), Evaluation of Federal Tax Incentives for Private R&D in Belgium: An Update, Federal Planning Bureau DP No 5-15, Brussels.

Fabrizio, K. (2009), Absorptive Capacity and the Search for Innovation, *Research Policy* 38(2), 255-267.

Fleming, L. and Sorenson, O. (2004), Science as a Map in Technological Search, *Strategic Management Journal* 25(8-9), 909–928.

Gambardella, A. (1995), *Science and Innovation: The U.S. Pharmaceutical Industry During the 1980s*. Cambridge University Press: Cambridge, U.K.

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

González, X. and Pazó, C. (2008), Do Public Subsidies Stimulate Private R&D Spending?, *Research Policy 37*(3), 371–389.

Görg, H. and Strobl, E. (2007), The Effect of R&D Subsidies on Private R&D, *Economica 74*(294), 215–234.

Griliches, Z. and Mairesse, J. (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.

Hottenrott, H. and Lopes-Bento, C. (2014), (International) R&D Collaboration and SMEs: The Effectiveness of Targeted Public R&D Support Schemes, *Research Policy* 43, 1055-1066.

Hottenrott, H. and Peters, B. (2012), Innovative Capability and Financing Constraints for Innovation: More Money, More Innovation?, *Review of Economics and Statistics* 94(4): 1126-1142.

Howitt, P. (1999), Steady Endogenous Growth with Population and R&D Inputs Growing, *Journal of Political Economy* 107, 715–730.

Jaffe, A.B. (1986), Technological Opportunity and Spillovers of R&D: Evidence From Firm's Patents, Profits, and Market value, *American Economic Review* 76(5), 984–1001.

Karlsson, M., Trygg, L. and Elfström, B.-O. (2004), Measuring R&D Productivity: Complementing the Picture by Focusing on Research Activities, *Technovation* 24, 179–186.

Lechner, M. (1998), Training the East German Labour Force: Microeconometric Evaluations of Continuous Vocational Training After Unification, Physica: Heidelberg.

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.

Mansfield, E., Rapoport, J., Schnee, J., Wagner, S. and Hamburger, M. (1971), *Research and Innovation in the Modern Corporation.* Norton: New York.

Nevo, R. (1998), *Trends and Patterns of Public Support to Industry in the OECD Area*, STI Review 21, 12-24.

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.

Pretschker, U. (1998), Public Support for Industrial R&D Efforts: The perspective of the Organisation for Economic Cooperation and Development (OECD), *Science and Engineering Ethics* 4(3), 363-374.

Usher, D. (1964), The Welfare Economics of Invention, *Econometrica* 31, 279–287.

Rosenberg, N. (1990), Why do Firms do Basic Research (With Their own Money)?, *Research Policy* 19, 165–174.

Rubin, D.B. (1977), Assignment to Treatment Group on the Basis of Covariate, *Journal of Educational Statistics* 2, 1-26.

Segerstrom, P.S. (2000), The Long-Run Growth Effects of R&D Subsidies, *Journal of Economic Growth* 5(3), 277-305.

Stock, J. and Yogo, M. (2005), Testing for Weak Instruments in Linear IV Regression, in: Andrews, D.W., editor, Identification and Inference for Econometric Models, 80–108, Cambridge University Press, New York.

Takalo, T., Tanayama, T., Toivanen O. (2013a), Estimating the Benefits of Targeted R&D Subsidies, *Review of Economics and Statistics* 95(1), 255 - 272.

Takalo, T., Tanayama, T., Toivanen O. (2013b), Market Failures and the Additionality Effects of Public Support to Private R&D: Theory and Empirical Implications, *International Journal of Industrial Organization* 31(5), 634 - 642.

Wallsten, S.J. (2000), The Effects of Government-Industry R&D Programs on Private R&D: the Case of the Small Business Innovation Research Program, *RAND Journal of Economics* 31(1), 82-100.

# Appendices

## Appendix 1: Matching Protocol

**Table A.1: The matching protocol**[18]

| | |
|---|---|
| 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. In our case, industry classification and year, for instance. This variant is called hybrid matching (see Lechner 1998). Furthermore, for the case of development grants, we use firm size as an additional criterion. |
| 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 $\Omega$ is the empirical covariance matrix of the matching arguments based on the sample of potential controls. 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 | Select the observation with the minimum distance from the remaining control group. (Do not remove the selected controls from the pool of potential controls, so that it can be used again.) If the control group is empty after applying the caliper threshold, the treated firm is dropped from the sample and is not taken into account in the evaluation. |
| 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. |

[18] The matching protocol follows Gerfin and Lechner (2002).

## Appendix 2: Additional descriptive statistics

### Table A.2: Industry distribution

| Industry | NACE (rev. 2008) | Description | Frequency | % |
|---|---|---|---|---|
| 1 | 10, 11, 12 | Food and Tobacco | 719 | 5.92 |
| 2 | 13, 14, 15 | Textiles, Clothing and Leather | 715 | 5.89 |
| 3 | 16, 31 | Wood and Furniture | 413 | 3.4 |
| 4 | 17, 18 | Paper | 484 | 3.99 |
| 5 | 19, 20 | Chemicals | 678 | 5.59 |
| 6 | 21 | Pharmaceuticals | 221 | 1.82 |
| 7 | 22 | Rubber and Plastic | 451 | 3.72 |
| 8 | 24, 25, 33 | Metal | 1,096 | 9.03 |
| 9 | 27, 28 | Machines and Equipment | 1,175 | 9.68 |
| 10 | 26 | ICT | 624 | 5.14 |
| 11 | 29, 30 | Transport | 697 | 5.74 |
| 12 | 41 | Building and Construction | 318 | 2.62 |
| 13 | 1, 5, 23, 37, 35, 32 | Miscellaneous Industries | 493 | 4.06 |
| 14 | 45, 46, 47, 49, 55, 58 | Commerce and Transport | 1,498 | 12.34 |
| 15 | 59, 64, 68, 69, 71 - 79 | Other Services | 1,179 | 9.71 |
| 16 | 61, 62 | Software Development and Communication | 1,377 | 11.34 |
| | | | 12,158 | 100.0 |

### Table A.3: Within-sample grant characteristics

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| *Grant frequency full sample (N = 12,138)* | | | | |
| Participants any scheme | 0.153 | 0.360 | 0 | 1 |
| Research grant | 0.044 | 0.204 | 0 | 1 |
| Development grant | 0.075 | 0.262 | 0 | 1 |
| Mixed grant | 0.062 | 0.242 | 0 | |
| | | | | |
| *Grant types of subsidy recipients (N =1,857)* | | | | |
| Research grant | 0.285 | 0.451 | 0 | 1 |
| Development grant | 0.487 | 0.500 | 0 | 1 |
| Mixed grant | 0.408 | 0.492 | 0 | 1 |
| Research grant (annual amt.) | 64.695 | 343.080 | 0 | 8,852.925 |
| Development grant (annual amt.) | 80.729 | 318.735 | 0 | 6,706.612 |
| Mixed grant (annual amt.) | 141.999 | 474.050 | 0 | 7,038.835 |
| Total amount yearly | 288.016 | 849.742 | 0.938 | 14,637.96 |

Note: Amounts in thousands of Euros. Total grant size distributed over grant duration and includes all grants per firm and year. N denotes firm-year observations.

**Table A.4a: Descriptive statistics by group of the control variables**

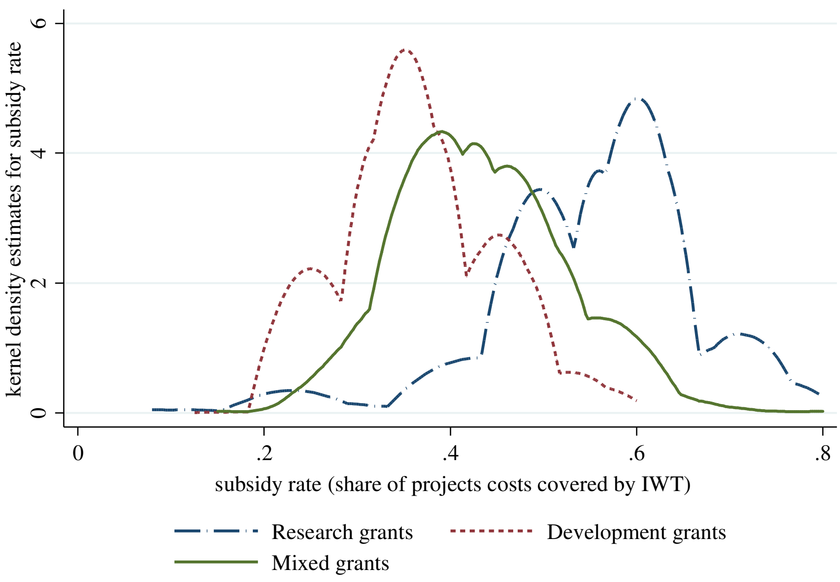
| | I<br>No grants<br>Control group<br>N = 10,281 | | II<br>Any grant[§]<br>$S_{rd}$<br>N = 1,563 | | III<br>Research grant<br>$S_r$<br>N = 336 | | IV<br>Develop. grant<br>$S_d$<br>N = 705 | | V<br>Mixed grant<br>$S_{mix}$<br>N = 522 | | VI<br>Multiple grants<br>$S_{mult}$<br>N = 294 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Control variables** | | | | | | | | | | | | |
| *R&D cooperation* | 0.085 | 0.278 | 0.332 | 0.471 | 0.313 | 0.464 | 0.245 | 0.431 | 0.462 | 0.499 | 0.585 | 0.494 |
| *Patent stock per employee* | 0.014 | 0.099 | 0.046 | 0.139 | 0.048 | 0.121 | 0.044 | 0.126 | 0.048 | 0.165 | 0.062 | 0.144 |
| *Labor productivity* | 391.71 | 1,126.51 | 273.66 | 328.43 | 232.28 | 277.16 | 256.35 | 343.84 | 323.68 | 332.01 | 302.29 | 282.29 |
| *Past research grants* | 0.022 | 0.147 | 0.124 | 0.330 | 0.182 | 0.386 | 0.102 | 0.303 | 0.117 | 0.322 | 0.395 | 0.490 |
| *Past development grants* | 0.033 | 0.179 | 0.138 | 0.345 | 0.134 | 0.341 | 0.193 | 0.395 | 0.065 | 0.247 | 0.435 | 0.497 |
| *Past mixed grants* | 0.017 | 0.128 | 0.154 | 0.361 | 0.119 | 0.324 | 0.089 | 0.285 | 0.264 | 0.441 | 0.568 | 0.496 |
| *Foreign group* | 0.199 | 0.400 | 0.217 | 0.412 | 0.182 | 0.386 | 0.155 | 0.362 | 0.324 | 0.468 | 0.286 | 0.453 |
| *SME* | 0.854 | 0.353 | 0.781 | 0.414 | 0.866 | 0.341 | 0.864 | 0.343 | 0.613 | 0.488 | 0.551 | 0.498 |
| *ln(Employees)* | 3.871 | 1.491 | 4.106 | 1.720 | 3.725 | 1.532 | 3.761 | 1.486 | 4.817 | 1.901 | 5.300 | 2.058 |
| *ln(Capital intensity)* | 3.110 | 1.249 | 3.035 | 1.129 | 3.057 | 1.135 | 3.003 | 1.123 | 3.063 | 1.134 | 3.099 | 0.998 |
| *ln(Age)* | 3.147 | 0.633 | 2.952 | 0.722 | 2.882 | 0.659 | 2.977 | 0.674 | 2.962 | 0.816 | 3.056 | 0.933 |

Notes: [§]contains firms with mixed grants only, research grants only and developments grants only, i.e. excludes multiple grants from different schemes. N refers to the number of firm-year observations.

**Table A4.b: T-tests on mean difference on the groups of control variables**

| | I vs II | I vs III | I vs IV | I vs V | I vs VI | III vs IV | III vs VI | IV vs VI | V vs VI |
|---|---|---|---|---|---|---|---|---|---|
| | **P-values of two-sided t-tests on mean differences of the groups of interest (Pr(\|T\| > \|t\|))** | | | | | | | | |
| | **Control variables** | | | | | | | | |
| *R&D cooperation* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.022 | 0.000 | 0.000 | 0.001 |
| *Patent stock per employee* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.641 | 0.178 | 0.049 | 0.222 |
| *Labor productivity* | 0.000 | 0.010 | 0.002 | 0.169 | 0.174 | 0.262 | 0.002 | 0.043 | 0.352 |
| *Past research grants* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *Past development grants* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.019 | 0.000 | 0.000 | 0.000 |
| *Past mixed grants* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.134 | 0.000 | 0.000 | 0.000 |
| *Foreign group* | 0.110 | 0.418 | 0.004 | 0.000 | 0.000 | 0.272 | 0.002 | 0.000 | 0.260 |
| *SME* | 0.000 | 0.550 | 0.491 | 0.000 | 0.000 | 0.921 | 0.000 | 0.000 | 0.084 |
| *ln(Employees)* | 0.000 | 0.079 | 0.059 | 0.000 | 0.000 | 0.720 | 0.000 | 0.000 | 0.001 |
| *ln(Capital intensity)* | 0.026 | 0.445 | 0.023 | 0.408 | 0.885 | 0.474 | 0.623 | 0.205 | 0.654 |
| *ln(Age)* | 0.000 | 0.000 | 0.000 | 0.000 | 0.017 | 0.032 | 0.007 | 0.137 | 0.134 |

**Figure A.1: Subsidy rates by scheme (1997–2011)**




Source: IWT ICAROS Database - own calculations

## Appendix 3: Potential selection on unobservables

The matching estimator only controls for the selection into grants on observables. To test whether the main conclusions hold if we account for a potential selection on unobservable factors, such as the innovation management qualities of the firms involved, we conduct instrumental variable (IV) regressions. Given that the receipt of a research subsidy might depend on different criteria than the receipt of development subsidies, we constructed separate instruments for each type of treatment. We instrument the receipt of a research grant by two variables, namely the mean amount of research subsidies granted to a certain industry in a given year and the number of research subsidies the focal firm received in the past. The rationale behind the former instrument is that the higher the amount of public support invested by the government in a given sector and year, the higher the probability that $firm_i$ will have received a subsidy if it was active in the same industry in the given time period. The second instrument is based on the rationale that firms that have had past subsidies in a certain scheme are more likely to apply and therefore be granted a subsidy in that scheme again. For the development treatment, our instruments are similar, but are based on the average amount of development subsidies by sector and year and past experience with development projects rather than research projects. As can be seen in Table A.5, all our instrumental variables pass the standard criteria of relevance and exogeneity (Stock and Yogo 2005). The results from the two-stage least squares regressions (2SLS) in Table 8 show that the previous conclusions on the strength of the cross effects, particularly the cross effect from development grants on net research, hold. In contrast to the matching estimator results, the direct effects are significant not only for research grants, but also for development grants. The tests for equality of coefficients in the research and the development equations suggest that both grant types have comparable effects in each equation. The estimates, however, suggest a similar direction as in the matching in terms of a significantly lower direct effect of development grants compared to research grants and a lower direct effect than cross effect for development grants.

**Table A.5: Instrumental variable regressions, N= 11,844, n = 1,986**

| | **ln(net research expenditures)** | **ln(net development expenditures)** |
|---|---|---|
| *ln(Research grant)* | 1.453 *** | 0.845 ** |
| | (0.383) | (0.364) |
| *ln(Development grant)* | 1.045 *** | 0.555 *** |
| | (0.172) | (0.175) |
| *R&D cooperation* | 1.235 *** | 0.845 *** |
| | (0.145) | (0.144) |
| *ln(Patent stock per employee)* | 0.921 | 1.748 ** |
| | (0.772) | (0.699) |
| *ln(Labor productivity)* | 0.392 *** | 0.365 *** |
| | (0.057) | (0.058) |
| *Foreign group* | 0.074 | -0.101 |
| | (0.132) | (0.129) |
| *ln(Employees)* | 0.071 | 0.071 |
| | (0.165) | (0.165) |
| *ln(Employees)$^2$* | 0.044 * | 0.057 ** |
| | (0.024) | (0.024) |
| *ln(Capital intensity)* | 0.068 | -0.059 |
| | (0.041) | (0.042) |
| *ln(Age)* | -0.149 | 0.586 |
| | (0.470) | (0.496) |
| *ln(Age)$^2$* | 0.015 | -0.083 |
| | (0.077) | (0.082) |
| *SME* | 0.003 | 0.182 |
| | (0.237) | (0.244) |
| *Constant* | -1.047 | -0.672 |
| | (0.847) | (0.889) |
| Uncentered $R^2$ | 0.526 | 0.616 |
| Joint sign. of industry dummies chi$^2$(15) | 34.94*** | 43.57*** |
| Joint sign. on time dummies chi$^2$(11) | 213.49*** | 441.34*** |
| F-test of excl. instr. (1$^{st}$ stage: R grant) | 12.76*** | 12.76*** |
| F-test of excl. instr. (1$^{st}$ stage: D grant) | 28.24*** | 28.24*** |
| Hansen J over identification test | 0.646 | 0.580 |

Note: Standard errors are clustered at the firm level. *** (**, *) indicate a significance level of 1% (5%, 10%). Firms with multiple grants from different schemes in the same year are excluded from both models (N = 294).