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(International) R&D Collaboration and SMEs: The Effectiveness of Targeted Public R&D Support Schemes

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Non-technical summary

It is today widely acknowledged that innovation constitutes one of the most important drivers of economic growth and competitiveness (see e.g. Solow, 1957; Griliches, 1979, 1992; Hall, 1996). Private sector firms' investment in R&D plays a crucial role in this process not only for the discovery of new technologies, but also for their diffusion.

Because of various well-known market failures though, it is unlikely that left alone, firms would invest the socially optimal amount in R&D. For this reason, governments design various policy schemes to stimulate investment in R&D. In Flanders, the northern part of Belgium, the government has spent 628 million euros on direct support for R&D and innovation for a total of 3,019 projects between 2002 and 2008. Thereby Flanders employs regional-specific policy design – i.e. a dual policy focusing on small and medium-sized firms (SMEs) on the one hand and (international) collaboration, on the other.

The present research aims, on the one hand at evaluating whether these targeted measures are efficient in terms of input additionality, and, on the other hand, whether they translate into innovation output. With respect to input, we find that subsidies accelerate R&D spending in the private sector. When analyzing the impact of the specific policy features on the treatment effect, we find evidence for the efficacy of the policy currently in use. In particular, we find that SMEs have a larger treatment effect than larger-sized firms. We further find that internationally collaborating SMEs have a larger treatment effect than internationally collaborating larger firms or non-internationally collaborating SMEs.

Further, we implement the results of the treatment effects analysis into a series of innovation output models, where R&D is disentangled into purely privately financed R&D (i.e. R&D expenditures that the firm would have spent in any case) and subsidy induced R&D expenditure. We find that both types have a significant positive effect on firms' innovativeness measured by their share of sales from market novelties. Further, when interacting both types of R&D investment with the specific policy features of the funding scheme under review, we find that the policy-triggered effect on market novelties is highest for internationally collaborating firms.

Das Wichtigste in Kürze

Forschung und Entwicklung (F&E) und die daraus resultierenden Innovationen leisten einen wesentlichen Beitrag zu Wirtschaftswachstum und Wettbewerbsfähigkeit von Volkswirtschaften (Solow, 1957; Griliches, 1979, 1992; Hall, 1996). F&E Aktivitäten des privaten Sektors spielen dabei eine zentrale Rolle nicht nur durch die Entwicklung neuer Technologien, sondern auch durch deren Verbreitung und Anwendung bei anderen Unternehmen und Verbrauchern.

Aufgrund von Marktversagen ist es jedoch unwahrscheinlich, dass private Unternehmen ohne weiteres das Niveau an F&E Investitionen tätigen, welches von gesamtgesellschaftlichen Standpunkt aus gesehen optimal wäre. Aus diesem Grund sind staatliche Subventionsprogramme verschiedener Art weit verbreitet, die zu Investitionen in F&E anregen und finanzielle Hürden abbauen sollen. In Flandern, dem nördlichen Teil Belgiens, betrugen die für solche direkten Förderprogramme im Zeitraum von 2002 bis 2008 aufgewandten Mittel 628 Millionen Euro für insgesamt 3,019 Projekte. Die Förderprogramme sind dabei derart gestaltet, dass sie den regional-spezifischen Faktoren der kleinen, offenen Volkswirtschaft Rechnung tragen sollen, indem kleine und mittlere Unternehmen sowie Firmen mit F&E in (intentionaler) Zusammenarbeit gezielt gefördert werden.

Die folgende Studie befasst sich mit der Bewertung der Effektivität dieser gezielten Förderprogramme, nämlich einerseits im Hinblick auf das Ziel F&E Tätigkeiten im privaten Sektor anzuregen und andererseits den Innovationserfolg der geförderten Unternehmen zu steigern. Die Ergebnisse zeigen, dass die gezielte Innovationspolitik in der Tat F&E Tätigkeiten im privaten Sektor anregt. Es zeigt sich dabei, dass die subventions-induzierte Steigerung der F&E-Intensität bei kleinen und mittleren Unternehmen größer ist als bei großen Unternehmen.. Die Ergebnisse zeigen zudem, dass international zusammenarbeitende kleine und mittlere Unternehmen (KMU) einen größeren „Treatmenteffekt“ erfahren als international zusammenarbeitende große Unternehmen oder nicht international zusammenarbeitende KMU. Darüber hinaus implementieren wir die geschätzten „Treatmenteffekte“ in einem weiteren Schritt unserer Analyse in eine Reihe von Modellen zur Einschätzung des Innovationserfolgs von Unternehmen. Dabei unterscheiden wir gezielt zwischen rein privaten F&E Investitionen und subventions-induzierter F&E. Die Ergebnisse verdeutlichen, dass beide Arten von F&E einen positiven Einfluss auf den Innovationserfolg, gemessen anhand des Umsatzanteils mit Marktneuheiten, haben. Des Weiteren lassen die Ergebnisse darauf schließen, dass die Produktivität induzierter F&E für international zusammenarbeitende Unternehmen am höchsten ist.

(International) R&D Collaboration and SMEs: The effectiveness of targeted public R&D support schemes*

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Abstract

This study analyses the effectiveness of targeted public support for R&D investment. In particular, we test whether the specific policy design aiming at incentivizing (international) collaboration and R&D in small and medium-sized firms achieves the desired objectives on input as well as output additionality. Our results show that the targeted R&D subsidies accelerate R&D spending in the private sector, and especially so in the targeted groups. Further, we differentiate between privately financed R&D and subsidy-induced R&D investment to evaluate their respective effects on innovation performance. The results confirm that the induced R&D is productive as it translates into marketable product innovations. While both types of R&D investments trigger significant output effects, we find that the effect of subsidy-induced R&D investment is higher for firms that collaborate internationally as well as for SMEs.

Keywords: Innovation Policy, Subsidies, R&D, SMEs, International Collaboration, Treatment Effects, Innovation Performance

JEL-Classification: C14, C30, H23, O31, O38

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1. INTRODUCTION

It is today widely acknowledged that private sector firms' investment in R&D plays a crucial role, not only for the discovery of new technologies, but also for their diffusion. Market failures, however, impede firms from investing the socially optimal amount in R&D, so that the private level of R&D-investment tends to be lower than socially desirable (Nelson, 1959; Arrow, 1962; Bloom at al., 2010). While the social returns to innovation can be substantial, it is not evident that at the project level the private returns to innovation investment are always positive. Moreover, uncertainty about the potential returns to R&D as well as information asymmetries between the firm and potential outside lenders and investors affect financing conditions for innovation projects. As a consequence, firms often have to rely on internal funds to finance innovation. However, if internal financing is limited, as is often the case especially for young and small- and medium-sized firms (SMEs), R&D projects may be foregone if these firms face binding financing constraints in capital markets (see Berger and Udell, 2002; Carpenter and Petersen, 2002; Hyytinen and Toivanen, 2005; Czarnitzki and Hottenrott, 2011b). Consequently, public policies are designed so as to reduce the cost of private R&D to incentivize firms to pursue socially valuable R&D projects that would not be carried out otherwise.

The present study is concerned with one specific public policy, namely direct financial support for R&D. While this question has been tackled at length by economic research, the suggested analysis goes beyond the questions that are commonly raised in this stream of literature. While most studies are primarily concerned with whether a subsidy has a positive effect on input and/or output additionality, our analysis evaluates firstly how the treatment effect is affected by specific policy features in place and secondly how the publicly induced part of the R&D investment translates subsequently into product market innovations.

In particular, we study the case of the innovation policy in place in Flanders (to be explained in detail in the following section), the northern part of Belgium, where direct subsidies are of particular interest, both in terms of their economic importance as well as in terms of the policy design. This policy differentiates itself from other policies in that it incorporates special features for SMEs and collaborating firms.

Even though the impact of collaborative R&D has received a lot of attention in the literature, *subsidized* collaborative R&D has received far less attention in the previous research to date. Exceptions are Sakakibara (2001) and Branstetter and Sakakibara (2002) who analyzed Japanese government-sponsored R&D consortia and both studies found evidence that participating firms have higher R&D expenditures as well as more patents. Further, Czarnitzki et al. (2007) apply a matching estimator in a multiple treatment setting analyzing the effects of R&D collaboration and public R&D funding on R&D per sales and patent outcomes for Germany and Finland and find that collaboration has positive effects. Likewise, only a few studies have been concerned with the difference in the effects of privately respectively publicly funded R&D. To the best of our knowledge, with the exceptions of Czarnitzki and Hussinger (2004) and Czarnitzki and Licht (2006) who find a positive impact of publicly induced R&D investment on German firms' patent activity, Hussinger (2008) who analyses the effects on new product sales also for German firms and Cerulli and Poti (2010) who explore the impact of a specific R&D policy tool in Italy, no other empirical paper explicitly distinguishes the privately invested from publicly induced R&D.

Neither of these studies, however, analyses to which extent the effects of privately or publicly funded R&D are driven by specific policy features, and how they differ between SMEs and larger firms. Hence, this study not only adds to previous research by evaluating specific features of current innovation policies on the treatment effect, but we further analyse if, and how, those elements translate into innovation performance and how this impact might be affected by firm size.

Our analysis confirms higher input additionality for SMEs and for internationally collaborating SMEs. Moreover, our findings point to significantly higher output additionality for international collaborators as compared to national collaborating firms or non-collaborators. In other words, the results show that the subsidy-triggered R&D expenditures do indeed lead to radical product innovations and especially so in the targeted groups.

The article proceeds as follows. Section 2 illustrates the Flemish policy design as well our research question. Section 3 reviews the related literature. The empirical research strategy will be described in section 4. Section 5 presents the data, section 6 discusses the results and section 7 concludes.

2. OUR RESEARCH QUESTION IN LIGHT OF FLEMISH INNOVATION POLICIES

In Flanders, the government has spent 628 million euros for a total of 3,019 projects between 2002 and 2008. The policies currently in place in Flanders comprise special features targeting SMEs as well as collaborating firms. The rationale of the former element of the current R&D policy is based on the argument that SMEs are more often financially constrained than larger firms. Yet, SMEs do contribute considerably to knowledge creation and technological progress as younger, smaller firms tend to engage in more basic and radical innovation projects (see e.g. Henderson and Clark, 1990; Henderson, 1993; Schneider and Veugelers, 2010; Haltiwanger et al, 2010). Furthermore, SMEs are an important source of job creation as they constitute the majority of firms in Flanders. Being aware of these aspects, the Flemish funding agency grants a higher subsidy to SMEs in order to incentivize them to become active in R&D or to enable them to pursue R&D projects at the desired level and scope. The rationale of the second policy element, i.e. granting higher subsidies to collaborating firms in order to increase incentives for such collaborations, is based on well-known arguments that stress the value of collaborations not only for triggering additional R&D spending, but also for enhancing R&D productivity (see next section for a literature review on these arguments as well as some main findings). In the case of Flanders, the benefits from collaboration, and in particular of the cross-border type, may even be particularly pronounced as in a small country the pool of knowledge a firm can dig in on national territory is usually limited. Firms may thus benefit from the larger pool of knowledge provided by international collaboration partners that facilitate spillovers from a richer pool of other R&D-active firms (Griliches, 1995). Moreover, international R&D collaboration promises additional gains through direct access to knowledge that is relevant for foreign markets. While off-shoring of own R&D abroad may be costly and subject to a liability of foreigners (Sofka and Schmidt, 2009), collaborating with partner firms that are already active in the target markets may therefore constitute a more cost-efficient way of doing R&D internationally. International collaboration may thus be particularly beneficial for firms active in global markets and firms that are “lonely riders” in their domestic markets. Moreover, SMEs may find collaborations to be an appealing strategy for the internationalization of their (R&D) activities.

The dual policy design employed by the Flemish funding agency thus targets SMEs on the one hand and (international) collaboration, on the other, aiming at achieving both high input as well as output additionality through increasing R&D investment and knowledge accessibility in otherwise constrained firms.

The general feature of the subsidy scheme of the agency for Innovation by Science and Technology in Flanders / Agentschap voor Innovatie door Wetenschap en Technologie in Vlaanderen (IWT), is its bottom-up character: it is a permanently open and non-thematic scheme. In other words, any firm can submit an R&D project at any time of the year.[1] Upon evaluation, the firm will get informed about whether or not the proposed project has been retained for public support. The evaluation is done by internal as well as external referees that evaluate the ex-ante effectiveness of the project proposals (ex-post evaluation is starting up). The subsidies are granted as matching grants, that is, the firm can apply with a specific project and in case of a successful referee process the government pays some share of the total cost, usually between 30 and 50%. This percentage can vary with respect to firm size or collaboration status. Indeed, the policies currently in place in Flanders comprise special features targeting SMEs as well as collaborating firms.

To support small and medium-sized firms in conducting R&D projects, the government covers a higher share of their total R&D project costs. In particular they receive an additional 10% of their total R&D costs. Likewise, in order to encourage firms to collaborate, an additional 10% of the total costs can be obtained if the firm collaborates with one or more partners for its R&D activities. This amount is again linked to firm size: If a firm qualifies as an SME, it receives a 10% top-up for national or international collaboration. If a firm qualifies as large-sized firm, it receives the additional 10% if at least one of its partners is an SME or an international partner.[2]

One concern with this type of direct support for R&D and innovation is of course that firms might use the subsidies to carry out projects with high excepted private returns, which would have been carried out even without the receipt of a subsidy. In this case, subsidies would not increase the overall R&D intensity in the economy, but would merely replace

[1] The scope of the IWT funding scheme is large, and also comprises funding programs for public research centers, universities and other institutes for higher education. However, given that this study focuses on firms, we refrain from going into detail on any of their other funding schemes.

[2] The background information is based on Larosse (2011), http://www.eurotransbio.eu and www.iwt.be, where further and more detailed information on the functioning on the IWT can be found.

private by public money, and one would face crowding-out effects.[3] By designing R&D support schemes in a way to best target firms with the highest crowding-in potential, governments aim at reducing the likelihood that public money is wasted. However, the ex-post effectiveness of the design is not obvious ex-ante.

In order to gain some novel insights on the ex-post effectiveness, we estimate in a first step whether we find evidence on input additionality. In a second step, we estimate whether the additional R&D induced by the public policy – controlling for other performance drivers – leads to higher innovation performance. Indeed, even if we were to find positive treatment effects and significant positive effects of specific policy features, it is not clear whether the undertaken projects induced by public support only have an impact on input additionality or whether they also impact output additionality, as measured for instance by product innovations. Based on the principle of portfolio maximization by companies, one would expect that firms chose to conduct the projects with the highest expected profits from their research portfolio first. Therefore, governmental entities support and thereby induce investment in R&D, in order to incentivize firms to also undertake riskier projects. These are likely to generate high social benefits, but would possibly not be undertaken without public support due to the high risk of failure and financing constraints associated with more radical R&D (Czarnitzki and Hottenrott, 2011a). Hence, the project evaluation by the Flemish government does not only concern the financial criteria of a submitted project, but also the social and economic return for Flanders (Larosse, 2011). In other words, the government also finances, or even favors, projects of more radical or basic research nature, generally linked to higher risks and financial constraints. If such policy is efficient, the likelihood of the selected projects to result in product innovations that can be labeled as market novelties should be quite high, given that the latter are generally driven by more radical R&D as opposed to

[3] See for instance Czarnitzki and Lopes-Bento (2012) for a more detailed overview on subsidy effects on input and output additionality.

incremental innovations resulting more often in products that are new to the firm, but not to the market. In this case, one could expect to see a positive significant effect of induced R&D investment on firms' sales from market novelties. On the other hand, however, it is not clear to which extent the risk of failure is appropriately taken into account by the government in its decision making process. In other words, if the government were to finance too many too risky projects or R&D that is too far from the market, one would not find a positive impact of publicly induced R&D on market novelties, even if we did find evidence of additional R&D triggered by the subsidy. Given these opposing arguments, it is not *a priori* clear what to expect with respect to the output additionality effect of the innovation policy in place.

3. RELATED LITERATURE

The impact of public policies on firms' innovative behaviour has attracted a lot of interest in the literature. On the one hand, these studies are concerned with whether or not crowding-out effects of private investment occur because of public financial support. In this stream of literature, Hall and Maffioli (2008) have concluded that since 2000, the only study having found evidence of total crowding-out is a study by Wallsten (2000) on the US Small Business Innovation Research (SBIR) program. The author finds total crowding-out of private money due to public support. However, he cannot reject the hypothesis that the grants allowed firms to continue their R&D activities at a constant level rather than cutting back. All the other studies find evidence for crowding-in effects. This is also the case for Flanders, where Aerts and Czarnitzki, 2006; Aerts and Schmidt, 2008 or Czarnitzki and Lopes-Bento, 2011, 2012 find evidence that public support stimulates private R&D investment.

On the other hand, a separate stream of research has expressed an increased interest in the impact of collaboration on innovation performance. Indeed, given the non-rival, non-exclusive character of knowledge, a firm can never appropriate all of the benefits of its R&D investment although it has to bear all of the costs (Arrow, 1962). Parts of the created knowledge are likely to spill over to competitors, so that many agents can benefit from the investment undertaken by one firm. Collaborating in R&D projects constitutes a way of limiting such involuntary spillover effects by allowing to internalize technological spillovers and thus increasing incentives for R&D investment (see e.g. Katz, 1986; d'Aspremont and Jacquemin, 1988; De Bondt and Veugelers, 1991; Kamien et al., 1992; Motta, 1992; Suzumura, 1992; Vonortas, 1994; Leahy and Neary, 1997). Empirical findings generally confirm the expected positive results of R&D collaboration. Janz et al. (2003), van Leeuwen (2002) and Criscuolo and Haskel (2003), for instance, find evidence of a positive correlation between R&D collaborations and innovation performance. Some other studies have been interested in the impact that the different contractual forms of these collaborations have on innovation performance (see e.g. Sakakibara, 1997; Hagedoorn and Narula, 1996; Hagedoorn, 2002) or partner type (see e.g. Belderbos et al., 2004; Cassiman and Veugelers, 2005) and find that there is heterogeneity in the goals pursued by the different collaborations. Second, collaboration allows exploiting economies of scale and scope in R&D and pooling of complementary technological skills if the firms involved combine resources in order to undertake larger, more complex, and more expensive research projects (Teece, 1992; Das et al., 1998; Rothaermel, 2001; Hemphill and Vonortas, 2003; Powell and Grodal, 2005). Synergetic effects and risk pooling can broaden the research horizon of collaborating firms. Indeed, risk can be substantial in R&D undertakings, especially when involving basic research and research aimed at radical innovations. Third, firms acquire new technological capabilities from their partners which extend the benefits beyond the joint project (Kogut, 1988; Hamel, 1991; Mody, 1993; Mowery et al., 1996).

The present study is among the first to combine both these strands of literature. In particular, we are investigating the effectiveness of a targeted financial support that focuses on collaborative R&D on the one hand, and firm size on the other. First, we test if we find evidence for crowding-in as well as whether the treatment effect of the subsidy scheme is affected by specific policy features aiming at incentivizing (international) collaboration and R&D in small and medium-sized firms. More precisely, extracting the treatment effect stemming from the receipt of a subsidy from a treatment effects analysis, we analyse if, and to what extent, these specific policy features have an impact on the magnitude of the estimated treatment effect. Further, disentangling privately financed from policy-induced R&D and interacting this with the specific policy features in place, we investigate whether the additional R&D induced by the subsidy scheme translates into higher innovation performance, and if the impact differs within the target and non-targeted groups.

4. ESTIMATION STRATEGY

4.1. Treatment Effects Analysis

The aim of the first part of the following analysis is to estimate the treatment effect of a subsidy on an outcome variable of interest. In other words, we want to know if, and to which extent, the subsidy impacts R&D investment. In order to do so, we test for the effect of the subsidy receipt on the firms' internal R&D spending by conducting a treatment analysis.

Econometric evaluation techniques have been developed to address the estimation of treatment effects when the available observations on individuals or firms are subject to a potential selection bias (see Heckman et al., 1999; Imbens and Wooldridge, 2009, for surveys). This typically occurs when participants of a public policy measure differ from non-participants in important characteristics. Different estimation strategies include the (conditional) difference-in-difference estimator, control function approaches (selection models), instrumental variable (IV) estimation, non-parametric (matching) techniques based on propensity scores and others such as regression discontinuity designs. Given that we do not have panel data, methods like the difference-in-difference cannot be used in our case. As a consequence, we will use matching techniques, which have the advantage over selection models not to need assumptions about functional forms and error term distributions. Based on the probability of receiving a treatment (obtained from a probit regression) conditional on a set of observable characteristics *X,* the propensity score is an index function summarizing in a single number (the score) the wide set of observable characteristics affecting the probability of receiving a treatment (i.e. a subsidy by the Flemish government). Matching on the propensity score has the advantage not to run into the "curse of dimensionality" since we use only one single index as matching argument (see Rosenbaum and Rubin, 1983).[4]

The fundamental evaluation question can be illustrated by an equation describing the average treatment effect on the treated firms:

$$\alpha^{TT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(R\&D_i^T - \widehat{R\&D_i^c}\right) \tag{1}$$

where $R\&D_i^T$ indicates the expenditure of treated firms and $\widehat{R\&D_i^c}$ the counterfactual situation, i.e. the potential outcome which would have been realized if the treatment group ($S=1$) had not been treated. In other words, for the untreated firms, $\widehat{R\&D_i^c}$ corresponds to their internal R&D expenditures. $S \in \{0,1\}$ indicates the receipt of a subsidy and N^T the number of treated firms.

For the matching estimator to be valid, we have to build on the conditional independence assumption introduced by Rubin (1977). That is, we have to observe all the important determinants driving the selection into program participation, namely the receipt of an IWT subsidy. In other words, after conditioning on *X*, the setting comes close to an experimental setting, and we have no *a priori* judgement about whether a firm receives or does not receive a treatment. Based on this assumption, we can estimate the counterfactual situation by using a selected group of non-subsidized firms that have similar characteristics in *X*:

[4] Matching estimators have been applied and discussed by many scholars, amongst which Angrist (1998), Dehejia and Wahba (1999), Heckman et al. (1997, 1998a, 1998b), Lechner (1999, 2000) and Smith and Todd (2005).

$$E(\text{R\&D}^{C} \mid S=1, X) = E(\text{R\&D}^{C} \mid S=0, X) \qquad (2)$$

and the average treatment effect on the treated can be written as:

$$\alpha^{TT} = E(\text{R\&D}^{T} \mid S=1, X=x) - E(\text{R\&D}^{C} \mid S=0, X=x) \qquad (3)$$

The construction of the control group depends on the algorithm chosen to conduct the matching. In the present analysis, we conduct a variant of the nearest neighbour propensity score matching, namely caliper matching.[5] Furthermore, we allow for two rather than just one nearest neighbor in our matching routine.[6] In other words, we pair each subsidy recipient with the two closest non-recipients. The pairs are chosen based on the similarity in the estimated probability of receiving a subsidy stemming from a probit estimation on the dummy indicating the receipt of subsidies *S*. In addition of matching on the propensity score, we also require the observations of firms in the selected control group to belong to the same year and the same industry as the firms in the treatment group.

Finally, it is essential that there is enough overlap between the control and the treated group (common support). In practice, the samples of treated and controls are restricted to common support. We thus calculate the minimum and the maximum of the propensity scores of the potential control group, and delete observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group.

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[5] Caliper matching aims at reducing the bias by avoiding to match treated firms with control firms above a certain “distance”, i.e. those firms for which the value of the matching argument Z_j is far from Z_i. It does so by imposing a predefined threshold □, above which an observation is deleted from the potential control group. More precisely, $\|Z_j - Z_i\| <$ □ for a match to be chosen (see Smith and Todd, 2005).

[6] The rationale of drawing two rather than just one nearest neighbor is to avoid that the results suffer from small sample sizes (we have 272 subsidized firms in our final sample, after the common support and caliper conditions). Despite the fact that two neighbors sensibly increase the bias when compared to using only one neighbor, all our covariates remain perfectly balanced after the matching. We can thus conclude that we have a rich enough control group to find 2 close neighbors for each treated firm and that the increase in the bias is negligible. The reduction in the variance of the estimates induced by the use of a second neighbor, allowing for a smaller asymptotic mean squared error, is more important than the increase in the bias. Note that equation 1 is adjusted accordingly.

The details of our matching routine are summarized in the protocol (following Gerfin and Lechner, 2002) presented in Table A1 in Appendix 1.[7]

4.2. Innovation Performance Anlysis

In this second part of the analysis, we estimate whether the additional R&D induced by the public policy not only leads to more R&D input, but also to more R&D outcome. In other words, we investigate the effect of the "additionality" of an IWT subsidy on innovation performance. We measure innovation performance by the firms' success in bringing innovations to the market, i.e. by the share of sales that can be attributed to products that were new to the market. Such market novelties are not only an indicator for successful R&D outcome, but also reflect the radicalness of the underlying R&D. Incremental R&D may rather result in product-range innovations that may be new to the firm, but to the market.

Given that not every firm has market novelty sales, the outcome variable *NOVEL* is left censored. We therefore estimate Tobit models to account for this censoring. Since the subsidies are matching grants where the percentage of covered costs can vary, it is not sufficient to divide R&D expenditures into the amount of privately financed R&D and subsidized R&D. Instead, one has to split R&D investment into the amount that a firm would have invested anyways and the part that is induced by the policy as indicated in Equation 1. In other words, we separate R&D expenditures into two components: R&D expenditures which would have taken place even if the subsidy scheme was not in place ($\widehat{R\&D}^C$) and those expenditures that were induced by the subsidy (α^{TT}).

Using α^{TT}, we estimate whether the acceleration in R&D induced by the subsidy (provided that $\alpha^{TT} > 0$) also triggers an increase in output additionality, as measured by sold

[7] Even though we think that our set of covariates allows us to assume that selection on *un*observable effects is unlikely, we report a robustness check concerning our main findings using IV regressions. This allows us to assess whether the results still hold even if we abandon the CIA. The results of the IV regressions as well as the choice of employed instruments are presented in Appendix 2.

market novelties. In order to obtain the estimated treatment effect at the level of the individual firm, we calculate the difference between the overall R&D investment and the counterfactual R&D investment as follows:

$$\alpha_i^{TT} = R\&D_i - \widehat{R\&D}_i^c \qquad (5)$$

For non-subsidized firms $\widehat{R\&D}_i^c$ is equal to their R&D intensity and α_i^{TT} is equal to 0.

The Tobit model to be estimated can be written as:

$$NOVEL^* = X'\beta + \varepsilon, \qquad (6)$$

where $NOVEL^*$ is the unobserved latent variable. The observed dependent variable is equal to

$$NOVEL = \begin{cases} NOVEL^* \; if \; X'\beta + \varepsilon > 0 \\ 0 \; otherwise \end{cases} \qquad (7)$$

where X represents a matrix of regressors, β the parameters to be estimated and ε the random error term. Since the standard Tobit model requires the assumption of homoscedasticity in order for the estimates to be consistent (see Wooldridge 2002: 533-535), we conducted several tests on heteroscedasticity using a heteroscedastic specification in the Tobit model. The Likelihood Ratio tests confirm the presence of heteroscedasticity. Hence, we estimated the heteroscedasticity-robust model by a maximum likelihood function in which we replace the homoscedastic standard error term σ with $\sigma_i = \sigma \exp(Z'\alpha)$ in the likelihood function. We included size class dummies based on the number of employees and industry dummies to model group-wise multiplicative heteroscedasticity.

Finally, given that the measures of R&D are estimated values for the treated firms, ordinary standard errors would be biased downwards and using them as covariates would induce measurement error. Therefore, we conduct the procedure 200 times to obtain bootstrapped standard errors for the Tobit estimates. It should be noted that the entire estimation is bootstrapped 200 times, i.e. including the matching routine. In other words, the bootstrap takes the sample as the population and the estimates of the sample as true values for all the steps of our estimation. This procedure thus allows us to estimate how the sample mean of our actual sample of size of 1,533 observations varies due to random sampling.[8]

5. DATA AND VARIABLES

The data used for the following analysis stem from the Community Innovation Survey (CIS) from the Belgian region of Flanders.[9] More precisely, they stem from three distinct waves of the CIS. First, the CIS4, covering the years 2002-2004, second the CIS5, covering 2004-2006 and third the CIS6 that refers to the period 2006-2008. This data has been complemented by accounting data from the Belfirst dataset issued by Bureau Van Dijk. Finally, information on R&D subsidies has been retrieved from the ICAROS database of the Flemish agency for innovation and technology (IWT). The latter provides detailed information on the amounts of the grants (and grant history) as well as on the duration of the funded projects.

After elimination of missing values, our final sample consists of 1,973 year-firm observations (referring to 1,593 different firms) and comprises innovative as well as non-innovative firms, covering manufacturing as well as business related services sectors.[10] Tables A.2 and A.3 in Appendix 1 show the industry structure as well as the firm size distribution of the firms in the sample. In this final sample, 300 firms received a public R&D subsidy from the Flemish government.

[8] Note that due to missing values in the dependent variable (*NOVEL*), the number of observations drops from 1,973 to 1,533 observations in this part of the analysis.

[9] The CIS covers all of the EU member states, Norway and Iceland using a largely harmonized questionnaire throughout participating countries.

[10] According to the 3rd edition of the Oslo Manual – which is the definition followed by the CIS - an innovative firm is one that has implemented an innovation during the period under review. An innovation is defined as the implementation of a new or significantly improved product (good or service) or process or service (see OECD/Eurostat, 2005).

Outcome variables

In the first part of our analysis, we consider R&D investment, i.e. the ratio of internal R&D expenditures[11] to sales (multiplied by 100) as the outcome variable *(RDINT)*. In the second part, estimating firms' innovation performance, the outcome variable is defined as sales generated from market novelties as percent of total sales (*NOVEL*).

Explanatory variables

The receipt of a subsidy form the IWT is denoted by a dummy variable equal to one for firms that received public R&D funding and zero otherwise (*SUBS*). Moreover, we employ several control variables in our analysis that are likely to influence the selection into a public funding scheme or the firms' innovation performance. The number of employees (*EMPL*) takes into account possible size effects. We also allow for a potential non-linear relationship by including ($\ln EMPL^2$). As the firm size distribution is skewed, these variables enter in logarithms. We further include a dummy variable that is equal to one if a firm qualifies as an SME (*SME*).[12]

In addition, we include a dummy variable capturing whether or not a firm is part of an enterprise group (*GP*). Firms that belong to a group may have a lower incentive to apply for subsidies since firms that have a large majority shareholder do not qualify for the SME program in which higher subsidy rates are granted, even if they are small. In contrast, firms belonging to a group may benefit from better communication structures and thus are better informed about possible funding sources including public technology policy programs. Furthermore, firms belonging to a larger network may be preferred by the funding agency as the group membership possibly promises knowledge spillovers and thus economies of scope from the R&D process to a larger extent than for stand-alone companies. This might be even

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

[12] According to the EU's definition, an SME should have less than 250 employees and has either sales less than 50 million euros (or a balance sheet total of less than 43 million euros).

more pronounced for firms that have an (international) network. For this reason, we account in addition for the collaboration patterns at the sector level, capturing the collaboration propensity in the different industries and sub-regions (*COOP_industry*). In other words, that variable takes into account that firms active in certain industries might be more prone to engage into collaboration agreements, susceptible to influence both the likelihood of applying as well as of receiving a subsidy. Subsidiaries with a foreign parent (*FOREIGN*) may be less likely to receive subsidies as the parent may prefer to apply in its home country or because the funding agency gives preference to local firms. Furthermore, foreign parents with Flemish subsidiaries are typically large multinational companies and thus the local subsidiary does not qualify for special SME-support which reduces its likelihood to apply. As a consequence, it is *a priori* unclear whether the effect of these variables is positive or negative because of the opposing arguments outlined above.

The log of the firm's age (ln*AGE*) is included in the analysis as older firms may be more reluctant to pursue innovation, and hence are less likely to apply for R&D funding, all else constant. Furthermore, younger firms may be more likely to apply given that they are more likely to be financially constrained.

R&D experience, especially if successful, may be a crucial determinant of applying for public subsidy schemes for future projects. Moreover, it may increase chances of a proposal being approved if governments adopt a picking-the-winner strategy and favour firms with previously successful R&D. Patents may thus signal R&D quality and increase chances for future project proposals to be granted. To capture these dynamics, we include the firms' past patent stock (*PS*) in our regression. The patent information stems from the database of the European Patent Office (EPO). Patent stocks are computed as a time series of patent applications with a 15% rate of obsolescence of knowledge capital, as is common in the literature (see e.g. Griliches and Mairesse, 1984; Jaffe, 1986):

$$PS_{i,t} = (1-\delta)PS_{i,t-1} + PATAPPL_{i,t} \tag{8}$$

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 (*PS/EMP*).

Often governments do not only look at previous experience with conducting R&D projects when attributing a subsidy to a firm, but also at previous experience with a specific funding scheme. Hence, we also control for publicly supported R&D projects in the past. We include a variable equal to the number of IWT co-funded projects a firm has completed within the three preceding years (*IWT_PAST3YRS*).

We also control for the firms' activities in foreign markets and hence international competition by including a dummy equal to one if a firm is export active (*EXPORT*). Firms that engage more heavily in foreign markets may be more innovative than others (Bernard and Jensen 1999, 2004) and, hence, more likely to apply for subsidies. We further include the labour productivity as a covariate, measured as sales per employee, *LABPRO*, since high labour productivity may be a relevant determinant for receiving public funds if the government follows a picking-the-winner strategy rigorously.

We further control for the firms' collaboration activity. We can derive directly from the survey whether a firm collaborated for its R&D activities (*CO*). In addition, firms are asked to indicate the partner's location. Thus, we identify international collaborators as firms that have at least one partner outside of Belgium (*CO_INTERNAT*) and national collaborators as firms that have exclusively Belgian collaborating partners *(CO_NATIONAL).*

Finally, ten industry dummies control for unobserved heterogeneity and technological opportunity across sectors and three time dummies, one for each wave of the survey, are included to capture macroeconomic shocks.

Timing of variables

Given that each wave of the survey covers a three-year period, we employ lagged values wherever possible in order to avoid direct simultaneity between the dependent variables and the covariates to the largest possible extent. For instance, if the dependent variables are measured in period *t*, then *EMP*, *PS/EMP*, *LABPRO* and *EXPORT* are measured at the beginning of the survey period, i.e. in *t-2*.

Attributes that are usually highly persistent over time, like the information on *GP* and *FOREIGN,* are available such that they refer to the whole 3-year period, i.e. *t-2* to *t*. For instance, "Did your firm belong to a group during the period 2004-2006?". Likewise, we consider *AGE* as truly exogenous and hence it is measured in period *t*.

Descriptive statistics

Table 1 shows the descriptive statistics for the variables employed at the first stage of our analysis. As shown by the t-tests, almost all variable means are significantly different between the treated and the non-treated firms.

Table 1: Descriptive statistics

		***Subsidized* firms, N = 300**		***Unsubsidized* firms, N = 1,673**		***t-test* on diff. in means**
Variables	Unit	Mean	Std. Dev.	Mean	Std. Dev.	
Control variables						
COOP_industry	Ratio	0.569	0.216	0.469	0.261	***
SUBS_past3yrs	count	0.750	2.418	0.055	0.282	***
*PS/EMP*1000*	PS/empl	18.389	39.732	3.236	15.902	***
ln(EMP)	head count	4.634	1.897	3.881	1.396	***
EXPORT	dummy	0.540	0.499	0.433	0.496	***
GROUP	dummy	0.663	0.473	0.552	0.497	***
FOREIGN	dummy	0.283	0.451	0.288	0.453	
ln(AGE)	Years	3.130	0.891	3.136	0.835	
SME	dummy	0.633	0.483	0.812	0.391	***
CO_NATIONAL	dummy	0.657	0.476	0.307	0.461	***
CO_INTERNATIONAL	dummy	0.180	0.384	0.111	0.315	**
Outcome variable						
RDINT	Ratio	7.932	13.244	2.436	8.629	***

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

For instance, on average, treated firms are larger than non-treated firms. While, on average, a treated firm has some 100 employees, an untreated firm employs about 45. Treated firms also belong more often to a group and are more export oriented than non-treated firms. Furthermore, we can see that while a non-treated firm has 3 patents per 1000 employees, a treated group has on average 6 times more patents per 1000 employee. In addition, subsidized firms belong more often to an industry prone to collaborate and engage significantly more in collaboration agreements, both nationally and internationally. For instance, while 66% of treated firms engage into national collaboration agreements (18% in international ones), less than half as many untreated firms engage into national collaborations, with a mere 30% (with 11% engaging into cross-border collaboration). Further, treated firms have had more previously government co-funded projects. Interestingly, we do not see a difference between the shares of firms with a foreign headquarter in the subsidized and un-subsidized sub-samples and no difference in terms of average firm age and labor productivity. With respect to the outcome variable (*RDINT*), we find - as expected – that subsidized firms are more R&D-intensive. At this point, however, it is not clear how much of this difference can be attributed to the financial support provided by the subsidy and how much to the fact that R&D-active companies are more likely to apply for R&D subsidies.

6. EMPIRICAL FINDINGS

6.1. The Average Treatment Effect on the Treated

As previously explained, in order to apply the matching estimator, we first estimate a probit model to obtain the predicted probability of receiving a grant from the Flemish funding agency. As we can see in Table 2, with the exception of labor productivity and belonging to a group, all of our covariates are statistically significant and hence important characteristics in driving the selection into the public funding scheme. Even though the share of collaborators by industry is not individually significant, a test on joint significance on the share of collaborators, national collaborators and international collaborators displays highly significant results ($\chi^2(3)$ = 85.61***). As a consequence, we let all three controls enter the model. The same is true for the size variables. Even though they are not individually significant, jointly the test displays that these characteristics should be controlled for ($\chi^2(3)$ = 20.80***).

Table 2: Probit results on the selection into the treatment (*SUBS*) 1,973 obs.

Variables	**Coef.**	**Std. Err.**
COOP_industry	0.150	0.202
SUBS_past3yrs	0.613 ***	0.083
*PS/EMP*1000*	8.802 ***	1.570
ln(EMP)	-0.104	0.119
ln(EMP)^2	0.027 **	0.013
EXPORT	0.405 ***	0.135
GROUP	-0.004	0.107
FOREIGN	-0.419 ***	0.113
ln(AGE)	-0.092 *	0.054
SME	0.024	0.159
CO_NATIONAL	0.800 ***	0.131
CO_INTERNATIONAL	0.855 ***	0.110
ln(LABPRO)	0.022	0.067
Log-Likelihood	-599.207	
Joint sig. of time dummies	χ^2 (2) = 16.10***	
Joint sign. of industry dummies	χ^2 (9) = 56.74***	

Notes: *** (**, *) indicate a significance level of 1% (5%,10%). The model contains a constant, industry and year dummies (not presented).

We also included interaction terms between the policy feature characteristics, i.e. between size and collaboration status. However, the latter were neither individually nor jointly significant. As a consequence, we dropped them from the probit estimation (joint significance of *SME*NATONLY* and *SME*COLINT* is rejected with $\chi^2(2)$ = 4.00).

A precondition for the matching to be valid is to have common support. We reinforced this condition by imposing a caliper. In total, we lose 17 observations because of the common support condition and 11 because of the caliper. Our final sample hence consists of 272 subsidized firms.

As displayed in Table 3, all our covariates are well balanced after the matching as we no longer find significant differences in the variable means. We can thus conclude that our matching was successful. The only difference that remains is in our outcome variable. Hence, we can conclude that this difference can be attributed to the treatment, and that we can reject the null hypothesis of total crowding-out. The estimated treatment effect on R&D intensity amounts to 3.033 percentage points, which is very similar to previously found treatment effects for Flemish firms.

Table 3: Matching results

	***Subsidized* firms** N = 272		***Selected control group*** N = 533[13]		***t-test* on diff. in means**
Variables	Mean	Std. Dev.	Mean	Std. Dev.	
Control variables					
COOP_industry	0.570	0.222	0.569	0.217	
SUBS_past3yrs	0.287	0.686	0.272	0.645	
*PS/EMP*1000*	0.015	0.033	0.012	0.034	
ln(EMP)	4.464	1.778	4.370	1.707	
EXPORT	0.570	0.495	0.583	0.493	
GROUP	0.643	0.480	0.621	0.486	
FOREIGN	0.268	0.444	0.272	0.445	
ln(AGE)	3.102	0.874	3.025	0.852	
SME	0.662	0.474	0.664	0.473	
CO_NATIONAL	0.191	0.393	0.199	0.400	
CO_INTERNATIONAL	0.632	0.483	0.619	0.486	
ln(LABPRO)	5.265	0.696	5.286	0.745	
Outcome variable					
RDINT	7.098	11.907	4.065	11.249	***

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

6.2. The impact of specific policy features on the estimated treatment effects

A central question that arises from the design of the Flemish innovation policy is whether the specific features do indeed have the desired positive impact on the estimated treatment effect.

[13] The reason that the control group does not correspond to 544 observations is due to the fact that there was no second close enough neighbor for every treated firm.

Using the obtained treatment effect from the matching estimation as our new dependent variable, we run several OLS regressions in order to analyze the impact of certain specific policy features on the treatment effect. In order to do so, we regress the individual treatment effect α_i^{TT} on firm size and collaboration dummies. Besides the policy design dummies, we further control for the number of subsidized project a single firm has at the same time. Indeed, it is possible for a same firm to submit several projects and hence to get subsidies for more than one project at the same time. Based on the findings of Czarnitzki and Lopes-Bento (2012), concluding that the treatment effect increases with the number of subsidized projects a firm has at the same time, we control for this possibility by including a variable taking into account the number of simultaneously financed projects one firm has *(SUB_PROJECTS*).[14] The equation to be estimated can be expressed as:

$$\alpha_i^{TT} = \beta_0 + \sum\nolimits_1^m \beta(policy\_design\_dummies)_i + \beta_n(SUB\_PROJECTS)_i + \varepsilon, \qquad (9)$$

where the *m* policy design dummies comprise: (i) an SME dummy, (ii) two dummies equal to one if a firm qualifies as a small respectively a medium-sized firm, (iii) two dummies for national, respectively international collaboration as well as (iv) dummies for specific collaboration partner location. 48% of the firms in our sample do engage in some form of collaborative R&D. 12% collaborate with other firms in Belgium, but not with firms abroad. 36% have at least one international partner. These partners are located in within the European Union in most cases (for 87% of the firms). 34% have a partner in the US and 20% somewhere in the rest of the world. Of course firms can have multiple partners in several locations. Descriptive statistics of these variables are presented in Table A.4 in Appendix 1.

[14] The number of simultaneously financed projects enters the equation as a slope coefficient, having the same slope for all the firms in the sample, independent of firm size or collaboration status. When interacting the number of financed projects with firm size, for instance, we did not find evidence that the slope would be significantly different for large rather than medium or small sized firms. We thus leave this variable in without interacting it with other firm characteristics.

The results of the impact of collaboration status and firm size are displayed in Table 4. As we can see in Model 1, SMEs have on average a higher treatment effect compared to larger firms. In Model 2 the effect of collaborating (differentiating between national and international collaboration) is included. While qualifying as an SME remains highly significant, being engaged in (international) collaboration does not display any significant impact on the magnitude of the treatment effect. These conclusions hold when differentiating between small and medium sized firms in Model 3. However, we do not find a significant difference between the coefficients of small and medium firms (see test at the bottom of Table 4), reaffirming the effectiveness of an overall SME policy.[15] In light of these findings and given the important number of SMEs in the Flemish region, one interesting question would be to assess whether internationally collaborating SMEs differ in their treatment effect from other firms. For this purpose, we introduce interaction terms between size and international collaboration status. While the current policy offers a higher subsidy rate to collaborators provided that at least one qualifies as an SME *or* one is an international partner, we are interested in knowing whether further incentivizing international collaborating SMEs would display significant impacts. Especially for SMEs, cross-border collaboration may be an appealing strategy to internationalize their R&D activities. When introducing an interaction term between being an SME and an international collaborator in Model 4, we indeed find that the coefficient is positive, albeit only at a 10% level. When separating between small and medium-sized firms in Model 5, we find a positive interaction term for both, small as well as medium-sized firms. These findings suggest that special features for SMEs that engage into cross-border collaboration might be effective. In other words, the current R&D policy may be more effective if it targeted international R&D collaboration in

[15] According to the EU's definition, a firm qualifies as small-sized firm if it has fewer than 50 employees and a turnover of less than 10 million euros or a balance sheet total of less than 10 million euros. A firm is considered medium-sized if it employs between 50 and 250 employees and has a turnover of more than 10 but less than 50 million euros. See Table A.2 for details on the size distribution of the firms in our sample.

SMEs more directly or intensively. Put differently, instead of incentivizing partnerships with either an SME *or* an international partner, the policy could pay closer attention to partnerships within international SMEs.

Table 4: OLS regressions on the impact of size and collaboration on the individual treatment effect α_i^{TT} (N = 272)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
SME	4.104 ***	5.433 ***		1.181	
	(1.257)	(1.571)		(1.610)	
SMALL			3.703 *		-0.620
			(1.894)		(2.070)
MEDIUM			6.594 **		1.006
			(2.172)		(1.808)
CO_INTERNATIONAL		2.671	1.776	-0.905	-2.647
		(2.252)	(2.236)	(1.241)	(1.782)
CO_NATIONAL		-1.842	-1.616	-1.587	-1.544
		(2.332)	(2.343)	(2.359)	(2.320)
*SME*CO_INTERNAT*				4.485 *	
				(2.429)	
*SMALL*CO_INTERNAT*§					6.528 *
					(3.490)
*MEDIUM*CO_INTERNAT*§					7.515 **
					(3.315)
US					
EU					
RoW					
#SUB_PROJECTS	0.537 ***	0.477 **	0.426 **	0.507 ***	0.489 ***
	(0.199)	(0.188)	(0.181)	(0.191)	(0.188)
Overall model significance	6.72**	3.80**	3.21**	3.18 ***	2.59 **
Test *SMALL = MEDIUM* (*§interactions)*			1.22		§0.47

6.3. The impact on innovation performance

We turn next to our assessment of innovation performance, measured as sales generated from market novelties as percent of total sales. Specifically, we report in Table 5 the results of the heteroscedasticity-robust Tobit model on *NOVEL.* The average sales share from *NOVEL* in our sample is 9.77 (percent of turnover). Table 5 presents the average value for *NOVEL* for different sub-samples and reveals interesting differences between these groups. SMEs achieve a significantly higher share of their turnover from market novelties compared to larger firms (10.27 versus 8.13). Likewise, collaborating firms show higher values than non-collaborators (11.11 versus 8.30). Interestingly, the difference is only significant for international collaborators, not for firms with national partners only. Finally, we see that the sales share from market novelties within the group of subsidized firms is on average 5 percentage points higher than within non-subsidized firms.

Table 5: Market novelties in targeted groups

	*NOVEL**			
Variable	# obs.	Mean	Std. dev.	one-sided t-test
SME = 1	1,175	10.27	17.2	**
SME = 0	358	8.13	14.92	
CO = 1	801	11.11	17.78	***
CO = 0	732	8.30	15.35	
CO_INTERNAT = 1	610	11.63	17.66	***
CO_INTERNAT = 0	923	8.54	15.95	
CO_NATIONAL = 1	191	9.45	18.09	
CO_NATIONAL = 0	1,342	9.82	16.52	
SUBS = 1	270	13.64	18.77	***
SUBS = 0	1,263	8.94	16.13	

*Note that the total sample size is reduced to 1,533 for *NOVEL* due to missing values.

We can see that in all the Models presented in Tables 6a and 6b, the R&D spending in the counterfactual situation ($\widehat{R\&D^C}$) - i.e. R&D spending in absence of the subsidy - exhibits a significant positive effect on the share of sales from market novelties. For instance, we can see that in Model 1, an increase of 10% in the counterfactual R&D intensity would lead to an increase of 5 percentage points in the estimated latent dependent variable, i.e. the estimated sales share in market novelties, on average. Furthermore, Model 1 shows that the subsidy triggers R&D, having a positive impact on sales in market novelties. With respect to the coefficient, we find that is it similar in size to the coefficient of the privately induced R&D. In other words, the impact inflicted by private and public R&D investment is of similar magnitude. On top of estimating the effects of privately financed and publicly induced R&D, Model 1 shows that collaborating has a positive effect on *NOVEL*. Collaborating in R&D activities induces, on average, an increase in the estimated sales share from market novelties by 6 percentage points. When interacting collaboration with the privately ($\widehat{R\&D^C}*CO$) as well as the publicly induced part of R&D ($CO*\alpha^{TT}$), we see that the privately financed R&D is significant for both collaborating as well as non-collaborating firms. The policy-induced investment, however, is only significant for collaborators (Model 2).

In Model 3, we go a step further and distinguish between national and international collaboration. We can see that the significant result of collaboration was driven by international collaboration as it captured the full effect from collaboration in general and the coefficient of *CO_NATIONAL* is insignificant. In Model 4 we distinguish between partner locations and find that having a partner within the EU has a significant impact on sales in market novelties.

When interacting both types of R&D investment with international collaboration (Model 5), we find that the private part of the R&D investment is significant for both, international collaborators as well as for the other firms, whereas the policy-induced part only displays a significant result when received by international collaborators. In other words, while the private part of invested R&D always has a positive impact of marketable products, the governmental support only displays an effect when the recipient firm collaborates with one or more partners. This finding may suggest that knowledge spillovers from partner firms contribute substantially to the firms' success when introducing radical innovations. This may be attributed to the fact that, in line with the policy's objective, firms' may be incentivized to undertake riskier, more basic and more radical R&D projects, which are also more resource intensive and therefore might only become feasible when undertaken by consortia. Being engaged in collaboration contributes to both increased incentives to invest in R&D as freeriding is reduced and higher R&D productivity as a result of pooled of knowledge and exploitation of complementary assets.

In order to be able to assess whether international collaboration has an added value compared to national collaboration only, we reduce the sample to collaborating firms only in Model 6. While in Model 5 the term *1-CO_INTERNAT* included also non-collaborating firms, in Model 6, it will capture exclusively national collaborators. The results show that for both types of collaboration, the firms' R&D spending is more productive if the firm is engaged in international collaboration as compared to national collaboration only, reaffirming our previous findings.[16]

In Model 7 we interact $\widehat{R\&D^C}$ and the treatment effect with the SME dummy. We see that both types of R&D investment have a significantly positive effect on *NOVEL* for SMEs when compared to large firms.[17] As could already be gathered by the descriptive statistics, this was to be expected. Indeed, it is often smaller and younger firms that undertake more basic and more radical research, able to translate into market novelties.

Finally, we find for all models that age and size have a non-linear effect, with a significant negative impact on market novelties sales for larger firms up to about 115 employees and for older firms up to about 17 years of age. This finding is in line with our expectations, given that often younger and smaller firms pursue more radical innovation that make up for a larger share of market novelty sales. We also controlled for other characteristics likely to influence market novelty sales like for instance the patent stock per

[16] We also tested the effect of national collaboration versus no collaboration in the sub sample of firms that excluded international collaboration. The interaction slope coefficients of *CO_NATIONAL* and the policy induced investment is statistically not significant, neither for national nor for non-collaborators. These results confirm insights from Model 6 that the added-value stems for international collaboration. Therefore, the results are not reported in detail.

[17] We also tested whether there was an effect if one differentiates between small and medium sized firms individually given the large number of SMEs in our sample. However, there is no significant difference between small and medium firms in terms of the productivity of the policy-induced R&D. Therefore, we do not report the results in details.

employee and the number of competitors, as well as for headquarter location. Given that we did not find significant effects for these variables, they were not included in the final models.

Table 6a: Heteroscedasticity-robust Tobit results on innovation success (*NOVEL*)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
$\widehat{R\&D}^C$	0.494 ***		0.494 ***	0.472 ***		
	(0.125)		(0.124)	0.127		
TREATM. EFFECT α^{TT}	0.525 **		0.515 **	0.515 **		
	(0.218)		(0.221)	0.231		
CO	6.207 **	6.413 *				
	(2.718)	(3.361)				
*CO**$\widehat{R\&D}^C$		0.476 ***				
		(0.175)				
*(1-CO)**$\widehat{R\&D}^C$		0.559 *				
		(0.295)				
*CO**α^{TT}		0.536 **				
		(0.232)				
*(1-CO)**α^{TT}		0.371				
		(0.833)				
CO_INTERNAT			6.980 ***		7.266 **	3.242
			(2.673)		(3.054)	(2.715)
*CO_INTERNAT**$\widehat{R\&D}^C$					0.453 ***	0.418 **
					(0.155)	(0.162)
*(1-CO_INTERNAT)**$\widehat{R\&D}^C$					0.591 **	0.312
					(0.267)	(0.847)
*CO_INTERNAT**α^{TT}					0.578 **	0.506 **
					(0.253)	(0.219)
*(1-CO_INTERNAT)**α^{TT}					0.289	0.147
					(0.494)	(0.888)
CO_NATIONAL			3.872	3.534	3.928	
			(3.623)	(3.470)	(3.716)	
ln(AGE)	-8.566 **	-8.451 **	-8.784 **	-8.667 **	-8.656 **	-3.688
	(3.790)	(3.741)	(3.930)	(3.875)	(3.869)	(3.411)
ln(AGE)^2	1.499 **	1.484 **	1.536 **	1.549 **	1.513 **	0.670
	(0.669)	(0.662)	(0.694)	(0.688)	(0.680)	(0.511)
ln(EMP)	-5.499 **	-5.459 **	-5.635 **	-5.577 **	-5.518 **	-6.695
	(2.469)	(2.449)	(2.592)	(2.591)	(2.511)	(4.231)
ln(EMP)^2	0.579 **	0.574 **	0.583 **	0.566 **	0.570 **	0.753
	(0.259)	(0.256)	(0.275)	(0.276)	(0.266)	(0.484)
EU_PARTNER				6.049 **		
				(2.530)		
RoW_PARTNER				-0.091		
				(1.960)		
US_PARTNER				2.408		
				(1.575)		
# observations	1,533	1,533	1,533	1,533	1,533	801[18]
$\hat{\sigma}$	16.236 ***	16.199 ***	16.370 ***	16.228 ***	16.123 ***	8.062 ***
	(3.905)	(3.884)	(4.025)	(4.017)	(3.849)	(2.438)

[18] In Model 6, the sample is reduced to collaborating firms only, reducing the number of observations to 801 observations.

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Standard deviations in parentheses are bootstrapped (200 replications). Time dummies (industry dummies) are jointly significant in the individual models in each replication of the Tobit models. All models contain a constant, industry and year dummies (not presented).

Table 6b: Heteroscedasticity-robust Tobit results on innovation success (*NOVEL*)

Variables	**Model 7**
$SME*\widehat{R\&D}^C$	0.671 ***
	(0.205)
$(1\text{-}SME)*\widehat{R\&D}^C$	0.206
	(0.489)
$SME*\alpha^{TT}$	0.506 *
	(0.306)
$(1\text{-}SME)*\alpha^{TT}$	0.503
	(1.578)
SME	4.648
	(4.064)
CO_INTERNAT	6.729 ***
	(2.407)
CO_NATIONAL	4.101
	(3.731)
ln(AGE)	-8.440 **
	(3.826)
$ln(AGE)^2$	1.452 **
	(0.652)
ln(EMP)	-5.346 **
	(2.450)
$ln(EMP)^2$	0.713 *
	(0.371)
# observations	1,533
$\hat{\sigma}$	16.556 ***
	(4.137)

Notes: See Table 5a.

Robustness check: taking the potential endogeneity of collaboration into account

One concern with these estimations could be that one of our core explanatory variables, namely collaboration, could potentially be endogenous. In order to test whether this is the case, we tested whether *CO_INTERNAT* and *CO_NATIONAL* are endogenous in a structural equation using the Smith and Blundell (1986) method for Tobit models. This method requires computing the residuals from the first stage reduced form regression (a probit model in our case) and subsequently plugging these residuals into the heteroscedastic-robust Tobit estimation of the market novelties equation. The usual t-statistic on the coefficient of the first stage residuals provides a test of the null hypothesis that the suspected variables are exogenous. Even though the original approach by Blundell and Smith was intended for continuous endogenous variables, the test for endogeneity remains valid of binary variables provided that the predicted residuals are generalized residuals. In that case, the error term is normally distributed under the null and the properties of the model remain valid.

For the purpose of this robustness check, we construct four instrumental variables (two for national and two others for international collaboration) that are correlated to the potentially endogenous variable, i.e. national and international collaboration, but exogenous to market novelties (*NOVEL*). For national collaboration the first instrument is defined as the share of nationally collaborating firms based in the same 2-digit-zip code area as firm *i* (*FIRM_NAT*). The rationale behind this instrument is that the higher the share of national collaborators in close proximity of firm *i*, the higher the probability that a firm engages into this type of collaboration. The second is defined as the share of nationally collaborating firms active in the same industry as firm *i* (based on a 2-digit NACE code) and situated in the same Flemish sub-region (*IND_CONAT*). The more firms active in a technology directly related to a firm *i*'s main activity and engaged in national collaboration, the higher the probability that the given firm engages in a collaborative agreement as well. The first instrument for international collaboration (*PC_COINT*), is defined as the share of internationally collaborating firms belonging to the same region (based on a 2-digit zip code) and the same industry (based on a 2-digit NACE code). In other words, this instrument captures the international collaboration propensity of firms in the same region belonging to the same industry. The more firms within geographic proximity and active in a technology directly related to a firm *i*'s main activity engage in international collaboration, the higher the probability that the given firm engages in an international collaborative agreement. Its sales share from market novelties, however, should be unaffected. The second instrumental variable for international collaborators (*YEXPINT*), captures the number of years of experience a firm has in international collaboration. A firm that collaborated internationally in the past is more likely to collaborate internationally in the future. As international collaboration may be more cumbersome than national collaboration, past experience might play a more important role for international rather than for national collaboration.

We tested for the statistical validity of our instruments, that is, whether the instruments are uncorrelated with the error term of the market novelties equation. Note, however, that there is no standard over-identification test for Tobit models like there is for linear models. Therefore, we can only perform a test by ignoring the left censoring of the market novelties variable. We used a standard Two Stage Least Squares (2SLS) model and computed Hansen's J test (the heteroscedasticity-robust version of the Sargan test). The Hansen J statistic is $\chi^2(1) = 1.179$ (p = 0.555) for the instruments on national collaboration and $\chi^2(1) = 0.776$ (p = 0.378) for the IVs of international collaboration. This indicates that our IVs satisfy the exogeneity requirement.

The results of this robustness check are displayed in Table 7. If the coefficient estimates are significantly different from zero, meaning the exogeneity of respective variables would be rejected, the second stage Tobit standard errors would not be asymptotically valid.

However, the first stage residuals are not significant in the *NOVEL* equation, which leads to the conclusion that the exogeneity of *CO_INTERNAT* and *CO-NATIONAL* is not rejected in our estimation on market novelties.

Table 7: Instrumental variable regressions for *NOVEL (1,533 obs.)*

Variable	**First stage: Probit on *CO_NATIONAL***	**First stage: Probit on *CO_INTERNATIONAL***	**Second stage: Tobit on *NOVEL* with 1st stage residuals (Blundell-Smith endogeneity test)**
FIRM_NAT (IV_1)	4.601 ***		
	0.409		
IND_CONAT (IV_2)	4.066 ***		
	0.480		
PC_COINT (IV_3)		2.589 ***	
		0.509	
YEXPINT (IV_4)		3.225 ***	
		0.256	
ln(AGE)	-0.492 **	0.230	-6.223 **
	0.252	0.344	2.714
ln(AGE)2	0.084 **	-0.028	1.040 **
	0.040	0.052	0.417
ln(EMP)	0.025	-0.209	-4.016 **
	0.140	0.163	1.717
ln(EMP)2	-0.008	0.017	0.405 **
	0.015	0.019	0.178
RDINT	-0.007	-0.002	0.475 ***
	0.005	0.005	0.124
CO_INTERNATIONAL			5.200 ***
			1.381
CO_NATIONAL			0.333
			4.155
1st stage resid. *NATIONAL*			0.740
			1.474
1st stage resid. *INTERNAT*			-1.002
			1.314

Notes: All stages include an intercept, time and industry dummies (not presented). Robust and clustered standard errors in parentheses. *** (**, *) indicate a significance level of 1% (5, 10%).

7. DISCUSSION AND CONCLUSIONS

The present paper provides new insides with respect to the evaluation of direct subsidies for R&D and innovation. The aim of the analysis was firstly to evaluate if specific policy features currently in use in Flanders are effective in terms of input additionality, and, secondly, whether the effect triggered by these policies also translates into higher output additionality.

With respect to input, we can, in line with the literature, reject the null hypothesis of total crowding-out of firms' own R&D efforts due to public support. We indeed find that subsidies accelerate R&D spending in the private sector. When analyzing the impact of the specific policy features on the treatment effect, we find evidence for the efficacy of the policy currently in use. The results show that SMEs do have a larger treatment effect than larger-sized firms. We further find that internationally collaborating SMEs have a larger treatment effect than internationally collaborating larger firms or non-internationally collaborating SMEs, and that there is no significant difference between small international collaborators versus medium-sized ones. This finding may provide the grounds on which the existing policy design can be improved so as to target these groups in particular, i.e. conditioning the percentage of costs covered not on either having an SME *or* and international partner, but further favor the firms that fulfill both conditions simultaneously.

The implementation of the results from the treatment effects analysis into a series of innovation output models brought forward additional insights. Both, privately financed as well as publicly induced R&D have significant positive effects on firms' innovativeness. Leading to more market novelties, these projects were presumably of more radical and basic nature (hence more risky), as opposed to rather incremental innovations. Further, we find that the policy-triggered effect on market novelties is highest for internationally collaborating firms. With respect to firm size, we find that both, privately as well as publicly induced R&D,

have a positive impact on sales from market novelties for SMEs. This is not necessarily surprising as smaller and younger firms often undertake more basic and radical innovation, which would be the kind of research resulting in product market novelties. Interesting is, however, that public subsidies seem to enhance innovation performance of SMEs beyond what could have been achieved in absence of the granted subsidy.

While this paper provides new insides to the effect of R&D policies on firms' innovative behavior, it has some caveats that ought to be addressed by future research. First, it would be advantageous to have longer time lags between the receipt of a subsidy and market novelty sales. Second, given that governments also aim at stimulating employment with their current policies, evaluating whether and to which extent the higher innovation performance translates into employment growth could constitute an interesting extension to this study. Third, it would be interesting to see if and how the results would be affected if partner type and mode of collaboration was taken into account (i.e. vertical vs. horizontal or diagonal collaborations). Finally, our results are based on data for the region of Flanders. It would thus be of particular interest for policy makers to know whether these findings are specific to Flanders, a small open economy, or whether some of these seemingly efficient policy features might also be effective in larger regions or countries.

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APPENDIXES

Appendix 1: Supplement tables

Table A1: The matching protocol

Step 1 Specify and estimate a probit model to obtain the propensity score $\hat{P}(X)$.

Step 2 Restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. This step is also performed for other covariates that are possibly used in addition to the propensity score as matching arguments. In our case, industry classification and year for instance. This variant is called hybrid matching (see Lechner, 1998).

Step 3 Choose one observation from the subsample of treated firms and delete it from that pool.

Step 4 Calculate the Mahalanobis distance between this firm and all non-subsidized firms in order to find the most similar control observation. $MD_{ij} = \left(Z_j - Z_i\right)' \Omega^{-1} \left(Z_j - Z_i\right)$

where Ω is the empirical covariance matrix of the matching arguments based on the sample of potential controls.

We use caliper matching, first introduced by Cochran and Rubin (1973). Caliper matching aims at reducing the bias by avoiding to match treated firms with control firms above a certain “distance”, i.e. those firms for which the value of the matching argument Zj is far from Zi. It does so by imposing a predefined threshold □. More precisely, ||Zj – Zi|| < □ for a match to be chosen (see also Todd and Smith, 2005). After calculating the distance, observations above this threshold are deleted from the potential control group. Similarly, since we require that for being a neighbor of treated firm *i*, the potential control observation has to belong to the same industry classification and year, firms belonging to other industries or years are deleted from the potential control group.

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.

Table A.2: Industry classification and distribution

	Industry Description	Freq.	in %	*CO*	*CO_INTERNAT*	*CO_NATIONAL*	*SUBS*
1	Food, beverages and tobacco	161	8.16	0.45	0.33	0.12	0.11
2	Textiles, clothing and leather	87	4.41	0.56	0.52	0.05	0.21
3	Chemicals (incl. pharma), rubber / plastics	199	10.09	0.66	0.57	0.09	0.21
4	Metal	170	8.62	0.51	0.36	0.15	0.21
5	Machinery and vehicles	218	11.05	0.52	0.43	0.09	0.22
6	Electronics, communication and instruments	140	7.10	0.61	0.44	0.16	0.31
7	Other manufacturing industries	410	20.78	0.39	0.25	0.15	0.06
8	Trade	259	13.13	0.39	0.29	0.10	0.04
9	ICT services	177	8.97	0.47	0.35	0.12	0.14
10	Other business services	152	7.70	0.45	0.28	0.17	0.24
		1,973	**100.00**				

Table A.3: Size distribution

Size classes		Freq.	in %	*CO*	*CO_INTERNATIONAL*	*CO_NATIONAL*	*SUBS*
1	< 20 empl.	42	2.13	0.35	0.22	0.14	0.11
2	≥ 20 empl. & < 50 empl.	137	6.94	0.40	0.41	0.28	0.13
3	≥ 50 empl. & < 100 empl	872	44.2	0.41	0.29	0.12	0.11
4	≥ 100 empl. & < 250 empl.	595	30.16	0.61	0.51	0.11	0.17
5	≥ 250 empl.	327	16.57	0.76	0.66	0.10	0.29
Total		**1,973**	**100.00**				

Table A.4: Descriptive statistics (1,973 obs.)

Variable	Unit	Mean	Std.	Min	Max
CO	*dummy*	0.483	0.500	0	1
CO_NATONLY	*dummy*	0.122	0.328	0	1
CO_INTERNAT	*dummy*	0.360	0.480	0	1
thereof					
EU_PARTNER	*dummy*	0.868	0.352	0	1
RoW_PARTNER	*dummy*	0.198	0.410	0	1
US_PARTNER	*dummy*	0.340	0.482	0	1
EU_HEADQUARTER	*dummy*	0.191	0.393	0	1
RoW_HEADQUARTER	*dummy*	0.028	0.165	0	1
US_HEADQUARTER	*dummy*	0.068	0.253	0	1
BE_HEADQUARTER	*dummy*	0.453	0.496	0	1
NOVEL~	*percentage*	9.771	16.714	0	100

Note: ~Available for 1,533 obs. only.

Appendix 2: Accounting for potential selection on unobservables

In order to test the robustness of our matching estimation, we complement the matching estimation by accounting for potential selection on unobservables using an IV regression.

In line with previous research on treatment effects analysis in a similar setting (see Czarnitzki and Lopes-Bento 2012), we use lags of the subsidy receipt as instrumental variables. In particular, we use "the number of subsidized projects that ended in period t-2" (*#PROJECTS*) along with their average size (equaling the "total amount of the subsidy in thousand euros" divided by the number of subsidized projects, *AV_AMOUNT*). Both instruments are relevant in the first stage on the receipt of a subsidy, and also pass the over-identification test (Hansen J-test) in the second stage. We thus conclude that they are valid to test for the robustness of our results if we abandon the conditional independence assumption. First, we estimate a two-stage least squares model. Second, we take into account that R&D-intensity is a censored as not all firms in our sample do conduct R&D in every period (or never). Therefore, we conduct an IV Tobit to take the censoring into account. Note that we estimate a heteroscedasticity-robust IV Tobit model due to evidence for violation of the homoscedasticity assumption (see Table A.5). Hence, we included size class dummies based on the number of employees and industry dummies to model group-wise multiplicative heteroscedasticity. We implement the IV estimation as a Full Information Maximum Likelihood estimator that estimates the two equations (main equation on R&D-intensity and the equation on the subsidy receipt) simultaneously (see Wooldridge, 2002, pp. 530-533 for details on the IV Tobit model)[19]. Moreover, our estimations take into account a possible correlation of error terms within repeated observation of the same firms by computing

[19] Note that in the FIML estimation, we use the number of subsidized projects rather than the dummy variable on whether or not a firm received a subsidy in order for the model to remain valid (Wooldridge (2002), p.531-533) .

clustered standard errors at the firm level. The results of the IV regression are presented in Table A.5.

As shown by Table A.5, our main results identified by the matching estimation remain valid when using IV regressions, controlling for unobserved heterogeneity. The effect of being subsidized (respectively on the number of subsidized projects) remains positive and statistically significant. While the coefficient of the OLS regression is substantially higher than the coefficient stemming from the matching estimation, we see that when the left censoring as well as the number of subsidized projects is taking into account, the results are in line with the one form the matching analysis.

Table A.5: Instrumental variable regressions for *R&D (1,973 obs.)*

	1st stage	2nd stage	
Variable	IWT_dummy	OLS on *RDINT*	IV Tobit on *RDINT*
AV_AMOUNT (IV_1)	<0.001 **		
	(0.000)		
#PROJECTS (IV_2)	0.090 ***		
	(0.035)		
SUBS		13.630 ***	
		(3.338)	
#SUBS_PROJ			1.069 ***
			(0.354)
COOP_industry	-0.024	-0.843	-1.285 **
	(0.031)	(0.989)	(0.561)
SME	0.018	1.145	-0.157
	(0.037)	(0.892)	(0.522)
CO_INTERNAT	0.157 ***	0.563	1.265 ***
	(0.020)	(0.777)	(0.577)
CO_NATIONAL	0.148 ***	-1.601 **	1.402 **
	(0.029)	(0.782)	(0.605)
*PS/EMP*1000*	2.685 ***	36.346 *	58.546 ***
	(0.528)	(21.998)	(16.127)
ln(AGE)	-0.013	-0.093	-0.382 **
	(0.010)	(0.228)	(0.184)
ln(EMP)	-0.054 *	0.486	3.462 ***
	(0.028)	(0.827)	(0.719)
ln(EMP)2	0.009 **	-0.106	-0.301 ***
	(0.004)	(0.097)	(0.063)
GROUP	0.010	0.836	0.089
	(0.020)	(0.615)	(0.388)
ln(LABPRO)	0.002	-1.196 ***	-1.075 ***
	(0.010)	(0.455)	(0.253)
FOREIGN	-0.069 ***	1.821 ***	0.172
	(0.023)	(0.790)	(0.379)
EXPORT	0.040 **	0.635	1.972 ***
	(0.019)	(0.592)	(0.500)
R2 / Log-Likelihood	0.361	0.207	-5,803.153
F-Test of excl. instruments	F(2, 1592) = 11.49	-	-
Hansen's J test statistic	$\chi^2(1)$ p = 0.245	-	-
Joint sign. of time Dummies	10.42***	16.18***	43.97***
Joint sign. of ind. dummies	4.68***	88.96***	359.27***
Joint sign. of ind. dummies & size class dummies in hetero term			155.17***

Notes: Both models include an intercept, time and industry dummies (not presented). Clustered standard errors in parentheses. The heteroscedasticity term includes the ten industry dummies and five size class dummies based on firms' employment. Note that the test on heteroscedasticity in the IV Tobit refers to heteroscedasticity in both estimated equations, the *RDINT* and the *SUBS* equation, simultaneously. *** (**, *) indicate a significance level of 1% (5%, 10%).