CEPS INSTEAD

WORKING PAPERS

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

Hanna HOTTENROTT[1, 2]
Cindy LOPES-BENTO[1, 2, 3]

K.U. Leuven, Belgium[1]
Centre for European Economic Research (ZEW), Germany[2]
CEPS/INSTEAD, Luxembourg[3]

Working Paper No 2012-36
October 2012

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

Hanna Hottenrott [a,b] and Cindy Lopes-Bento [a,b,c]

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

October 2012

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

	Hanna Hottenrott	Cindy Lopes-Bento
Address:	K.U.Leuven Dept. of Managerial Economics, Strategy and Innovation Naamsestraat 69, 3000 Leuven, Belgium	CEPS/INSTEAD 3, avenue de la Fonte L-4364 Esch-sur-Alzette Luxembourg
Phone:	+32 16 326 906	+352 58 58 55-406
Fax:	+32 16 326 732	+352 58 55 60
E-mail:	hanna.hottenrott@econ.kuleuven.be	cindy.lopesbento@ceps.lu

* **Acknowledgment**: We thank Dirk Czarnitzki, René Belderbos, Bernd Ebersberger, Alfonso Flores-Lagunes, Katrin Hussinger, Otto Toivanen, Philippe Van Kerm and Reinhilde Veugelers for helpful comments. Financial support from the IWT is gratefully acknowledged. Furthermore, Cindy Lopes-Bento gratefully acknowledges financial support from the Fonds National de la Recherche Luxembourg (FNR) and Hanna Hottenrott from the Research Foundation Flanders (FWO).

1. INTRODUCTION

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.

Market failures that impede firms from investing the socially optimal amount in R&D are therefore the grounds on which government programs to stimulate investment in R&D are generally justified. Indeed, 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. Given that firms cannot appropriate all returns from R&D, but have to bear the entire costs (Nelson, 1959; Arrow, 1962), the private level of R&D-investment is lower than socially desirable (Bloom at al., 2010). 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 subsidies[1] aim at reducing the cost of private R&D to incentivize firms to pursue socially valuable R&D projects that would not be carried out otherwise.

In Flanders, the northern part of Belgium, 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 (to be described in more detail in the following section) 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, rendering the pursuing of R&D projects more difficult for them. Yet, SMEs do contribute considerably to knowledge creation and technological progress because often 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). Furthermore, SMEs are an important source of job creation as they constitute the majority of firms in

[1] Direct subsidies for R&D constitute of course only one possible instrument to correct for the existing market failures. Other policies comprise intellectual property right systems to improve appropriability of knowledge, tax reliefs to reduce the cost of R&D (see Hall and Van Reenen, 2000), public venture capital (see Hall and Lerner, 2010 for a survey) or (public) loans with low interest rates.

Flanders. Being aware of these aspects, the 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 mainly on three arguments that stress the value of collaborations not only for triggering additional R&D spending, but also for enhancing R&D productivity. First, 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 by one firm. Collaborating in R&D projects constitutes a way of limiting such involuntary spillover effects, by allowing internalizing technological spillovers and thus increasing incentives for R&D investment as it reduces free-riding on R&D outcomes (Katz, 1986; d'Aspremont and Jacquemin, 1988; Kamien et al., 1992; Cassiman and Veugelers, 2002). 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. 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).

In the case of Flanders, the benefits from collaboration, and in particular of the cross-border type, may even be particularly pronouncedas in a small country or region, the pool of knowledge a firm can dig in on national territory is usually limited. Firms might 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 that targets SMEs on the one hand and (international) collaboration, on the other, thus aims at achieving both high input as well as output additionality through increasing R&D investment and knowledge accessibility in otherwise constrained firms.

2. RELATED LITERATURE

While a whole series of prior studies aimed at evaluating the effects of direct subsidies for R&D, most of the previous analyses concentrated mainly on crowding-out effects[2]. Most studies on the benefits of collaborative R&D or the impact of different collaboration partners (i.e. clients, competitors, suppliers, universities etc.) focused on overall innovation and firm performance without taking into account the role of specific innovation policies. Indeed, the literature on the effects on R&D collaboration is vast, from a theoretical as well as from an empirical point of view. The question of how and why firms engage in R&D collaborations – be it through partnerships, alliances, joint ventures or networks - and how that affects welfare, has emerged during the 1980s in the economic literature (see Veugelers, 1998 for a survey). Collaborative R&D has been acknowledged as a means of promoting private R&D and as a major tool for enhancing firm competitiveness (Sakakibara, 2001). A first strand of relevant literature relates to the models of industrial organization theory. This literature has primarily investigated the role of knowledge spillovers. In the absence of cooperation, knowledge spillovers are involuntary and may weaken the firm's relative market position by feeding knowledge to competitors. If engaged in R&D cooperation, these spillovers are internalized to the research consortia and diminish these free-riding effects. R&D collaborations thus represent one possibility to reduce this gap between private and social optimum in R&D investments by allowing firms to increase the appropriability of returns within the group of partners (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

[2] The literature on crowding-out effects is vast. Given that this is not the main scope of this paper, but merely the starting point, we are not going to elaborate on this literature in detail. For an overview of the most influential papers in the past two decades, we refer to Czarnitzki and Lopes-Bento (2012). For an overview on the various used methods see Cerulli (2010).

evidence of a positive correlation between R&D collaborations and innovation performance. Some other studies examined the effect of different cooperation types on various outcome variables of interest. Indeed, in light of the growing number of partnerships, the contractual forms of these collaborations have increasingly attracted attention in the economic literature (see e.g. Sakakibara, 1997; Hagedoorn and Narula, 1996; Hagedoorn, 2002). Belderbos et al. (2004), for example, analyze the impact of R&D collaboration on firm performance differentiating between four types of partners, namely competitors, suppliers, customers and universities and research centres. Their findings confirm a major heterogeneity in the goals pursued by the different collaborations. While competitors and suppliers concentrate more on incremental innovations (i.e. productivity growth, in the sense that they lead to higher sales of established products), cooperations with universities and with competitors are vital for achieving sales from market novelties. Cassiman and Veugelers (2005) find that there are large cross-industry differences in the probability of a firm collaborating with science. Firms that face high costs of innovation tend to be attracted by government subsidized cost-sharing in public-private partnerships. Moreover, larger firms are more likely to collaborate with universities than smaller firms, indicating that a minimum of absorptive capacity is necessary for the collaboration to be fruitful.

Finally, Grimpe and Sofka (2009) analyse search patterns of firms in the low- and medium-technology sectors which are much less studied in the literature than high-tech industries. Compared to previous studies, the authors design their analysis such as to connect the concepts of R&D investments and absorptive capacity with explicit patterns of search behaviour. They find that search patterns in low-technology industries are mainly determined by the market side and that they differ from technology sourcing activities in high-tech industries where search patterns emerge because of differences in technology sourcing.

While the literature on the impact of direct subsidies as well as the literature on the impact of collaborative agreements is vast, the combination of both, i.e. the impact of subsidized collaborative research is rather scarce. So far hardly any attention has been paid to the impact of subsidized (types of) collaboration or the impact of size-specific policies on the effect of a subsidy. Exceptions are Sakakibara (2001) and Branstatter and Sakakibara (2002) who analyze Japanese government-sponsored R&D consortia. Both studies find evidence that participating firms have greater 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.

As - to the best of our knowledge - apart from these studies no empirical evidence exists in such setting, the present study adds to previous work in at least two important dimensions. First, we explicitly analyse whether the treatment effect of the subsidy scheme is affected by the specific policy features aiming at incentivizing (international) collaboration and R&D in small and medium-sized firms. More precisely, extracting the treatment effect 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.

Second, disentangling private incentive-induced R&D from policy-induced R&D, we investigate whether the additional R&D induced by the subsidy scheme translates into higher innovation performance. Indeed, even if we were to find positive treatment effects, that is, a crowding-in due to the subsidy, it is not obvious that the additional R&D input will be productive in terms of marketable innovations.

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

3. OUR RESEARCH QUESTION IN LIGHT OF FLEMISH INNOVATION POLICIES

Most industrialized countries establish innovation policies to enhance firms' investments in R&D and innovation using various policy tools like for instance patent laws, tax incentives and/or direct subsidies. In Flanders, the government's main policy tool to correct for the existing market failures takes the form of direct subsidies for R&D. 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.[3] 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

[3] 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.

30 and 50%. This percentage can vary with respect to firm size or collaboration status. While a large part of private R&D investments is spent by large and established companies, the role of young, or small and medium-sized companies increasingly attracts policy makers' attention as their contribution to technological progress has been found to be substantial (Acs and Audretsch, 1990; Audretsch 2006). 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.[4]

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 private by public money, and one would face crowding-out effects.[5] By designing R&D support schemes in a way to best target firms with the highest crowding-in potential, governments aim to reduce the likelihood that public money is wasted. However, the ex-post effectiveness of the design is not obvious ex-ante.

Even though previous studies did not find evidence of crowding-out in the case of Flemish firms (see for instance Aerts and Czarnitzki, 2006; Aerts and Schmidt, 2008 or Czarnitzki and Lopes-Bento, 2011, 2012), in a first step, we analyze whether, in line with the literature, we can likewise reject the null hypothesis of total crowding-out given our sample of firms. This estimated treatment effect is then used to test the effectiveness of specific features of the Flemish innovation policy on the magnitude of the subsidy effect.

Second, 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

[4] The background information and stylized facts are 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.

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

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 in the free market. 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 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 sold 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. With the exception of studies by 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 and Cerulli and Poti (2010) who explore the impact of a specific R&D policy tool in Italy, we are not aware of any other empirical paper that explicitly distinguishes the privately invested from publicly induced R&D. Our study moreover adds to these previous ones as we further analyse to which extent the effects of either type of R&D investment are driven by specific policy features. Hence, this study not only adds to previous research by evaluating specific features of current innovation policies, but we further analyse if, and how, those elements translate into innovation performance.

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. For the research question and the dataset at hand, the most appropriate evaluation method is a non-parametric propensity score matching. 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). Furthermore, the matching estimator has the advantage over other models that it does not require any assumptions about functional forms and error term distributions.[6]

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

$$\alpha_{ATT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(R\&D_i^T - \widehat{R\&D}_i^c\right) \tag{1}$$

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. $S \epsilon \{0,1\}$ indicates the receipt of a subsidy and N^T the number of treated firms.

[6] 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).

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*:

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

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

$$\alpha_{ATT} = E(R\&D^T \mid S=1, X=x) - E(R\&D^C \mid S=0, X=x) \tag{3}$$

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.[7] Furthermore, we allow for two rather than just one nearest neighbor in our matching routine.[8] 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.

[7] 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 ε, above which an observation is deleted from the potential control group. More precisely, $\|Z_j - Z_i\| < \varepsilon$ for a match to be chosen (see Smith and Todd , 2005).

[8] 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 the increase in the bias is negligible and that 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.

The details of our matching routine are summarized in the protocol (following Gerfin and Lechner, 2002) presented in Table A1 in Appendix 1.[9]

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_{ATT}).

Using α_{ATT}, we estimate whether the acceleration in R&D triggered by the subsidy (provided that $\alpha_{ATT} > 0$) also triggers an increase in output additionality, as measured by sold 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:

[9] 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.

$$NOVEL^* = X' \beta + \varepsilon \,, \tag{6}$$

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

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

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 Greene, 2005), we conducted several tests on heteroscedasticity (Wald tests and LR tests) using a heteroscedastic specification in the Tobit model. We estimated this 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. The tests find evidence of hetero-scedasticity. We therefore only present the estimation results obtained from our heteroscedastic-consistent estimations.

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.[10]

5. DATA AND VARIABLES

The data used for the following analysis stem from the Community Innovation Survey (CIS) from the Belgian region of Flanders.[11] 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

[10] 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.

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

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.[12] 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.

Outcome variables

In the first part of our analysis, we consider R&D investment, i.e. the ratio of internal R&D expenditures[13] 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*).[14]

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

---

[12] 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).

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

[14] 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).

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 more pronounced for firms that have an international network. For this reason, we account in addition for the international collaboration patterns at the sector level, capturing the international collaboration propensity in the different industries and subregions (*INTCOOP_industry)*. In other words, that variable takes into account that firms close to borders, airports and harbours may be more likely to engage into international collaborations, 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):

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

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						
ln(EMPL)	head count	4.634	1.897	3.881	1.396	***
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	
ln(LABPRO)	turn/empl.	5.263	0.693	5.280	0.786	
EXPORT	dummy	0.540	0.499	0.433	0.496	***
INTCOOP_industry	ratio	0.411	0.241	0.310	0.235	***
SUBS_past3yrs	count	0.750	2.418	0.055	0.282	***
SME	dummy	0.633	0.027	0.812	0.010	***
CO_NATIONAL	dummy	0.650	0.028	0.279	0.011	***
CO_INTERNATIONAL	dummy	0.187	0.023	0.140	0.008	**
*PS/EMP*1000*	PS/empl	18.389	39.732	3.236	15.902	***
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, they belong more often to a group, have a higher patent stock per employee, are more likely to be export oriented, belong more often to an industry prone to collaborate internationally and engage significantly more in collaboration agreements, both nationally and internationally. Further, they 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, age 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 international collaborators by industry is not individually significant, a test on joint significance on the share of international collaborators, national collaborators and international collaborators displays highly significant results ($\chi^2(3)$ = 87.58***). 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 ($\chi^2(3)$ = 19.23***).

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

Variables	**Coef.**	**Std. Err.**
INTCOOP_industry	0.135	0.193
SUBS_past3yrs	0.615 ***	0.083
*PS/EMP*1000*	8.706 ***	1.571
ln(EMP)	-0.096	0.119
$ln(EMP)^2$	0.025 *	0.013

EXPORT	0.388 ***	0.135
GROUP	-0.014	0.107
FOREIGN	-0.434 ***	0.114
ln(AGE)	-0.088	0.054
SME	0.021	0.159
CO_NATIONAL	0.769 ***	0.121
CO_INTERNATIONAL	0.900 ***	0.110
ln(LABPRO)	0.019	0.067
Log-Likelihood	-598.362	
Joint sig. of time dummies	χ^2 (2) = 15.92***	
Joint sign. of industry dummies	χ^2 (10) = 55.77***	

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 $\chi^2(2) = 2.29$).

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 3.431 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 = 532[15]		***t-test* on diff. in means**
Variables	Mean	Std. Dev.	Mean	Std. Dev.	
Control variables					

[15] 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.

INTCOOP_industry	0.409	0.249	0.410	0.246	
SUBS_past3yrs	0.287	0.686	0.267	0.647	
*PS/EMP*1000*	0.015	0.034	0.013	0.035	
ln(EMP)	4.464	1.778	4.300	1.711	
EXPORT	0.574	0.495	0.575	0.495	
GROUP	0.643	0.480	0.601	0.490	
FOREIGN	0.268	0.444	0.248	0.432	
ln(AGE)	3.101	0.874	3.073	0.875	
SME	0.662	0.029	0.709	0.455	
CO_NATIONAL	0.199	0.401	0.201	0.400	
CO_INTERNATIONAL	0.625	0.485	0.618	0.486	
ln(LABPRO)	5.265	9.042	5.269	0.730	
Outcome variable					
RDINT	7.098	0.722	3.667	9.992	***

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. 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)*.[16] The equation to be estimated can be expressed as:

$$\alpha_i^{TT} = \beta_0 + \sum_1^m \beta(policy\_design\_dummies)_i + \beta_n(SUB\_PROJECTS)_i + \varepsilon, \qquad (9)$$

[16] 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.

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) a general collaboration dummy, (iv) two dummies for national, respectively international collaboration as well as (v) dummies for specific collaboration partner location. 48% of the firms in our sample do engage in some form of collaborative R&D. 15% collaborate with other firms in Belgium, but not with firms abroad. 34% have at least one international partner. These partners are located in within the European Union in most cases (for 93% of the firms). 37% have a partner in the US and 21% 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.

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 (*CO*), without differentiating between national and international collaboration, is included and has a (weak) positive effect on the magnitude of the treatment effect. When differentiating between international and national collaboration in Model 3, it turns out that this positive effect is driven by international collaboration rather than national collaboration only. The geographical location of the international collaboration partner, however, does not appear to have any significant impact on the treatment effect (Model 4).

We can thus conclude that the features of the Flemish innovation policy with respect to size and international collaboration are effective given these results. These conclusions are reaffirmed when the size effect is split between being a small and a medium-sized firm. We can see from Model 5 that both size dummies and international collaboration have a significant positive impact on the treatment effect. However, we do not find a significant difference between the coefficients of small and medium firms (see test at the bottom of Table 5), reaffirming the effectiveness of an overall SME policy.[17]

When introducing an interaction term between being an SME and an international collaborator in Model 6, we see that the positive significant effect gets absorbed by the interaction of being both, and the individual variables are no longer statistically significant. The interaction term (*SME*CO_INTERNAT*) itself, however, is positive and significant pointing to the conclusion that the treatment effect is significantly higher for SMEs that

[17] 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.

collaborate internationally compared to large internationally collaborating firms on the one hand, and non-internationally collaborating SMEs, on the other.

The previous findings supporting the efficiency of a more general SME policy are confirmed when introducing an interaction term of the small and medium size dummies with international collaboration (Model 7). Even though we find evidence for a larger treatment effect for internationally collaborating small and medium-sized firms, the test of equality of the coefficients of small and medium-sized international collaborators at the bottom of the table does not confirm a significant difference between both.

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

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
SME	3.037 ***	3.438 ***	4.527 ***	4.875 ***		0.482	
	(1.133))	(1.196)	(1.378)	(1.505)		(1.290)	
SMALL					3.723 **		-0.187
					(1.613)		(1.720)
MEDIUM					5.662 ***		0.970
					(1.917)		(1.805)
CO		2.814 *					
		(1.700)					
CO_INTERNATIONAL			4.163 **		3.634 **	0.112	-0.351
			(1.856)		(1.848)	(1.186)	(1.362)
CO_NATIONAL			-0.240		-0.087	-0.019	-0.066
			(2.034)		(2.058)	(2.020)	(2.066)
*SME*CO_INTERNAT*						5.107 **	
						(2.084)	
*SMALL*CO_INTERNAT*§							6.026 **
							(2.994)
*MEDIUM*CO_INTERNAT*§							6.408 **
							(3.031)
US				2.705			
				(2.122)			
EU				1.848			
				(1.846			
RoW				0.673			
				(2.134)			
#SUB_PROJECTS	0.508 ***	0.490 ***	0.436 ***	0.342 **	0.407 ***	0.475 ***	0.468 ***
	(0.177)	(0.174)	(0.162)	(0.180)	(0.156)	(0.166)	(0.162)
Overall model significance	6.01***	4.62***	4.29***	2.79***	3.93***	3.83 ***	2.87 ***
Test *SMALL = MEDIUM (§interactions)*					0.72		§0.01

Notes: *** (**, *) indicate a significance level of 1% (5%, 10%). Robust standard errors in parentheses are clustered accounting for repeated observations at the firm level. All models contain a constant.

6.3. The impact on innovation performance

The results of the heteroscedasticity-robust Tobit model on innovation success are reported in Table 5. We can see that in all the Models, 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% in the estimated latent dependent variable, i.e. the estimated sales share in market novelties, on average. While this result was to be expected from the part of the R&D expenditures a firm would have undertaken anyways (i.e. $\widehat{R\&D^C}$), the finding is less clear for the policy induced part of the spending. As we can see in Models 1 and 3 of Table 5, the policy induced part of innovation does have a positive and significant effect on *NOVEL*. On top of estimating the effects of privately financed and publicly induced R&D, Model 1 estimates what the effect of collaboration is on *NOVEL*. As we can see, collaborating has a direct effect on NOVEL as well. When interacting the fact of collaborating with the privately ($\widehat{R\&D^C}*CO$) as well as the publicly induced part of R&D ($CO*\alpha^{TT}$), we see that while the privately financed R&D is significant for both, collaborating as well as non-collaborating firms, the policy-induced investment only displays a significant results 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. In Model 4 we distinguish between partner locations. While partner location did not have an effect on input additionality, we see 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 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, this will capture exclusively national collaborators. The results show that indeed the induced part of the firms' R&D spending is more productive if the firm is engaged in international collaboration as compared to national collaboration only.[18] While privately financed R&D has a significant impact on *NOVEL* for national as well as for international collaborators, the policy induced part only displays a significant impact when received by international collaborators.

In Model 7 we interact $\widehat{R\&D^C}$ and the treatment effect with an SME dummy. We see that both types of R&D investment display a significant result for SMEs, but not for large firms.[19] Finally, we find 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 employee and the number of competitors. Given that we did not find significant effects for these variables, they were not included in the final models.

One concern with these estimations is 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. 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 (see Table A.6 in Appendix 3) which leads to the conclusion that the exogeneity of *CO_INTERNAT* and *CO-NATIONAL* is not rejected in our estimation on market novelties. The detailed estimation results of the endogeneity test as well as the choice of instrumental variables are reported in Table A.6 in Appendix 3.

[18] 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* with both R&D variables were not statistically larger than those of non-collaborators. They were even insignificant as was the *CO_NATIONAL* dummy. These results confirm insights from Model 6 and are therefore not reported in detail.

[19] 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, the results remained unchanged.

Table 5a: Heteroscedasticity-robust Tobit results on innovation success (*NOVEL*)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
$\widehat{R\&D}^C$	0.495 ***		0.486 ***			
	(0.124)		(0.124)			
TREATM. EFFECT α^{TT}	0.526 **		0.519 **			
	(0.213)		(0.221)			
CO	6.202 **	6.429 *				
	(2.716)	(3.371)				
*CO**$\widehat{R\&D}^C$		0.474 ***				
		(0.173)				
*(1-CO)**$\widehat{R\&D}^C$		0.576 *				
		(0.306)				
*CO**α^{TT}		0.556 **				
		(0.230)				
*(1-CO)**α^{TT}		0.060				
		(0.919)				
CO_INTERNAT			7.028 ***		7.481 **	4.053 **
			(2.658)		(3.193)	(1.882)
*CO_INTERNAT**$\widehat{R\&D}^C$				0.436	0.436 ***	0.613 ***
				(0.161)	(0.161)	(0.204)
*(1-CO_INTERNAT)**$\widehat{R\&D}^C$					0.634 **	1.256 **
					(0.286)	(0.635)
*CO_INTERNAT**α^{TT}					0.593 **	0.391 *
					(0.265)	(0.211)
*(1-CO_INTERNAT)**α^{TT}					-0.021	-0.325
					(0.548)	(0.844)
CO_NATIONAL			4.402	4.308	4.770	
			(3.653)	(3.613)	(4.016)	
ln(AGE)	-8.571 **	-8.465 **	-8.725 **	-8.856 **	-8.507 **	-2.391
	(3.794	(3.751)	(3.900)	(4.014)	(3.765)	(3.946)
ln(AGE)^2	1.500 **	1.483 **	1.530 **	1.571 **	1.493 **	0.339
	(0.670	(0.662)	(0.687)	(0.707)	(0.662)	(0.642)
ln(EMP)	-5.507 **	-5.491 **	-5.547 **	-5.606 **	-5.408 **	-1.373
	(2.476)	(2.476)	(2.536)	(2.603)	(2.434)	(3.371)
ln(EMP)^2	0.580 **	0.577 **	0.574 **	0.563 **	0.556 **	0.165
	(0.259)	(0.259)	(0.270)	(0.274)	(0.257)	(0.321)
EU_PARTNER				6.432 **		
				(2.765)		
RoW_PARTNER				-0.128		
				(1.971)		
US_PARTNER				2.524		
				(1.599)		
# observations	1,533	1,533	1,533	1,533	1,533	756

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 5b: Heteroscedasticity-robust Tobit results on innovation success (*NOVEL*)

Variables	**Model 7**
$SME*\widehat{R\&D}^C$	0.671 ***
	(0.210)
$(1\text{-}SME)*\widehat{R\&D}^C$	0.194
	(0.499)
$SME*\alpha^{TT}$	0.479 *
	(0.289)
$(1\text{-}SME)*\alpha^{TT}$	0.254
	(1.641)
$SMALL*\widehat{R\&D}^C$	
$MEDIUM*\widehat{R\&D}^C$	
$SMALL*\alpha^{TT}$	
$MEDIUM*\alpha^{TT}$	
SME	6.720
	(2.343)
SMALL	4.721
	(3.921)
CO_INTERNAT	4.593 ***
	(3.978)
CO_NATIONAL	
ln(AGE)	-8.324 **
	(3.744)
$ln(AGE)^2$	1.437 **
	(0.638)
ln(EMP)	-5.173 **
	(2.341)
$ln(EMP)^2$	0.694 *
	(0.356)
# observations	1,533

Notes: See Table 5a.

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 on the one hand to evaluate if specific policy features currently in use in Flanders are effective in terms of input additionality, and, on the other hand, 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 effects. 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. Indeed, we find that SMEs have a larger treatment effect than larger-sized firms. We further conclude from our results that in terms of collaboration, the effect is mainly driven by international collaboration rather than by national collaboration. Finally, we find that internationally collaborating SMEs have a larger treatment effect than internationally collaborating larger firms or non-internationally collaborating SMEs.

From the implementation of the results from the treatment effects analysis into a series of innovation output models, where R&D was disentangled into purely privately financed R&D (i.e. R&D expenditures that the firm would have spent in any case) on the one hand, and publicly induced R&D expenditure on the other hand, additional insights were won. We find that both, privately financed as well as publicly induced R&D has a significant positive effect on firms' innovativeness measured by their share of sales from market novelties. While a positive effect of R&D input on output was expected for the part of privately financed R&D investment, it was less clear whether the subsidy-induced R&D spending would trigger innovation performance. However, the results show that the policy-induced R&D investment likewise has a significant positive effect on innovativeness. Leading to more market novelties, those projects were presumably of more radical and basic nature (hence more risky), and hence would presumably not have been pursued in absence of the policy scheme.

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 an impact on sales in market novelties for SMEs. This is not necessarily surprising. Smaller and younger firms often undertake more basic and radical innovation, which would be the kind of research resulting into market novelties.

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) on top of partner location. 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.

REFERENCES

Acs, Z. and D. Audretsch (1990), *Innovation and Small Firms*, MIT Press, Boston.

Aerts, K. and D. Czarnitzki (2006), "The Impact of Public R&D–Funding in Flanders", *IWT Study No. 54*, Brussels.

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

Angrist, J. D. (1998), "Estimating the Labor Market Impact of Voluntary Military Service Using Social Security Data", *Econometrica* 66, 249-288.

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.

Audretsch, D. (2006), *Entrepreneurship, Innovation, and Economic Growth*, Edward Elgar Publishing, Chaltham.

Belderbos, R., Carree M. and B. Lokshin (2004), "Cooperative R&D and Firm Performance", *Research Policy* 33 1477-1492.

Berger, A. and G. Udell (2002), "Small Business Credit Availability and Relationship Lending: The Importance of Bank Organizational Structure", *Economic Journal* 112, 32-53.

Bernard, A. and J. Jensen (1999), "Exceptional exporter performance: cause, effect, or both?", *Journal of International Economics* 47(1), 1-25.

Bernard, A. and J. Jensen (2004), "Why Some Firms Export", *Review of Economics and Statistics* 86(2), 561-569.

Bloom, N., Schankerman, M. and J. Van Reenen (2010), "Identifying Technology Spillovers and Product Market Rivalry", *CEP Discussion Paper No 675*, initially February 2005, updated: September 2010, London.

Branstetter, L. G. and M. Sakakibara (2002), "When Do Research Consortia Work Well and Why? Evidence from Japanese Panel Data", *American Economic Review* 92(1), 143-159.

Carpenter, R. and B. Petersen (2002), "Capital Market Imperfections, High-Tech Investment, and New Equity Financing", *Economic Journal* 112, 54-72.

Cassiman, B. and R. Veugelers (2002), "R&D Co-operation and Spillovers: Some Empirical Evidence from Belgium", *American Economic Review* 92, 1169-1184.

Cassiman, B. and R. Veugelers (2005), "R&D Cooperation Between Firms and Universities. Some Empirical Evidence from Belgian Manufacturing", *International Journal of Industrial Organization* 23, 355– 379.

Cerulli, G. and B. Potì (2010), "The differential impact of privately and publicly funded R&D on R&D investment and innovation: The Italian case", *Working Papers 10, Doctoral School of Economics*, Sapienza University of Rome, revised 2010.

Cerulli, G. (2010), "Modelling and Measuring the Effect of Public Subsidies on Business R&D: a Critical Review of the Economic Literature", *Economic Record*, forthcoming.

Cochran, W. and D. Rubin (1973), “Controlling Bias in Observational Studies”, *Sankyha* 35, 417-446.

Criscuolo, C. and J. Haskel (2003), “Innovation and Productivity Growth in the UK: Evidence from CIS2 and CIS3”, *Working paper*, *Center for Research into Business Activity*.

Czarnitzki, D., B. Ebersberger and A. Fier (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. and H. Hottenrott (2011a), “Financial Constraints: Routine versus Cutting Edge R&D Investment”, *Journal of Economics & Management Strategy* 20(1), 121-157.

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

Czarnitzki, D. and C. Lopes-Bento (2011), “Evaluation of Public R&D Policies: A Cross-Country Comparison”, *World Review of Science, Technology and Sustainable Development*. 9, Nos.2/3/4, 2012.

Czarnitzki, D. and C. Lopes-Bento (2012), “Value for Money? New Microeconometric Evidence on Public R&D Grants in Flanders”, *Research Policy*, forthcoming.

Czarnitzki, D. and K. Hussinger (2004), “The Link between R&D Subsidies, R&D Spending and Technology Performance”, *ZEW Discussion Paper N. 04-56*, Mannheim.

Czarnitzki, D. and G. Licht (2006), “Additionality of Public R&D Grants in a Transition Economy: The Case of Eastern Germany”, *Economics of Transition* 14(1), 101-131.

d’Aspremont, C. and A. Jacquemin (1988), “Cooperative and Non-cooperative R&D in Duopoly with Spillovers”, *American Economic Review* 78(5), 1133-1137.

Das, S., Sen, P. K. and S. Sengupta (1998),” Impact of Strategic Alliances on Firm Valuation”, *Academy of Management Journal* 41, 27–41.

De Bondt, R. and R. Veugelers (1991), “Strategic investment with spillovers”, *European Journal of Political Economy* (7), 345-366.

Dehejia, R. H. and S. Wahba (1999), “Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs”, *Journal of the American Statistical Association* 94, 1053-1062.

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

Greene, W. H. 2005, *Econometric Analysis*, 5th edition, Prentice-Hall, New Jersey.

Griliches, Z. (1979), “Issues in Assessing the Contribution of Research and Development to Productivity Growth”, *Bell Journal of Economics* 10(1), 92-116.

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

Griliches, Z. (1992), “The Search for R&D Spillovers”, *Scandinavian Journal of Economics* 94, 29-47.

Griliches, Zvi, (1995), *R&D and Productivity*, in P. Stoneman (ed.), Handbook of Industrial Innovation, Blackwell Press, London.

Grimpe, C. and W. Sofka (2009), "Search Patterns and Absorptive Capacity: Low- and High-Tech Sectors in European Countries", *Research Policy* 38, 495-506.

Hagedoorn, J. (2002), "Inter-firm R&D Partnerships: an Overview of Major Trends, and Patterns Since 1960", *Research Policy* 34, 477-492.

Hagedoorn, J. and R. Narula (1996), "Choosing Organisational Modes of Strategic Technology Partnering: International and Sectoral Differences", *Journal of International Business Studies* (27), 265-284.

Hall, B. H. (1996), *The Private and Social Returns to Research and Development*, in: Smith, B. and C. Barfield (eds.), Technology, R&D, and the Economy, Brookings Institution and the American Enterprise Institute: Washington, DC.

Hall, B. H. and Van Reenen, J. (2000) "How Effective are Fiscal Incentives for R&D? A Review of the Evidence", *Research Policy* 29(4-5), 449-469.

Hall, B. H. and Lerner, J. (2010). The Financing of R&D and Innovation, in: Hall, B. and N. Rosenberg (Eds.), Handbook of the Economics of Innovation, Elsevier-North Holland.

Hamel, G. (1991), "Competition for Competence and Inter-partner Learning Within International Strategic Alliances", *Strategic Management Journal* 12, 83-103.

Heckman, J. J., R. J. Lalonde and J. A. Smith (1999), *The Economics and Econometrics of Active Labour Market Programs*, in: A. Aschenfelter and D. Card (eds.), Handbook of Labour Economics, Amsterdam, 3, 1866-2097.

Heckman, J. J., H. Ichimura and P. Todd (1997), "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a job Training Program", *Review of Economic Studies* 64(4), 605-654.

Heckman, J. J., H. Ichimura and P. Todd (1998a), "Matching as an Econometric Evaluation Estimator", *Review of Economic Studies* 65(2), 261-294.

Heckman, J. J., H. Ichimura, J. A. Smith and P. Todd (1998b), "Characterizing Selection Bias Using Experimental Data", *Econometrics* 66, 1017-1098.

Hemphill, T. and N. Vonortas (2003), "Strategic Research Partnerships: a Managerial Perspective", *Technology Analysis & Strategic Management* 15(2), 255-271.

Henderson, R. (1993), "Underinvestment and Incompetence as Responses to Radical Innovation: Evidence from the Photolithographic Industry", *Rand Journal of Economics* 24(2), 248-270.

Henderson, R. and K. Clark (1990), "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms", *Administrative Science Quarterly* 35, 9-30.

Hussinger, K. (2008), "R&D and Subsidies at the Firm Level: An Application of Parametric and Semiparametric two-step Selection Models", *Journal of Applied Econometrics* 23(6), 729–747.

Hyytinen, A. and O. Toivanen (2005), "Do financial constraints hold back innovation and growth?: Evidence on the role of public policy", *Research Policy* 34(9), 1385-1403.

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

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

Janz, N., Lööf H. and B. Peeters (2003), "Firm Level Innovation and Productivity – is There a Common Story Across Countries?" *ZEW Working Paper No. 03-26*, Mannheim.

Katz, M. L. (1986), "An Analysis of Cooperative Research and Development", *RAND Journal of Economics* 17(4), 527-543.

Kamien, M. I., Muller, E., and I. Zang (1992), "Research Joint Ventures and R&D Cartels", *American Economic Review* 82(5), 995-1012.

Kogut, B. (1988), "Joint Ventures: Theoretical and Empirical Perspectives", *Strategic Management Journal* 9, 319-332.

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

Leahy, D. and P. Neary (1997), "Public policy towards R&D in oligopolistic industries", *American Economic Review* (87)4, 642-662.

Lechner, M. (1999), "Earnings and Employment Effects of Continuous off-the-job Training in East Germany after Reunification", *Journal of Business and Economics Statistics* 17, 74-90.

Lechner, M. (2000), "An Evaluation of Public Sector Sponsored Continuous Vocational Training in East Germany", *Journal of Human Resources* 35, 347-375.

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

Mody, A. (1993), "Learning Through Alliances", *Journal of Economic Behavior and Organization* 20, 151–170.

Motta, M. (1992), "Co-operative R&D and vertical product differentiation", *International Journal of Industrial Organization* (10), 643-661.

Mowery, D. C., Oxley J. E. and B. S. Silverman (1996), "Strategic Alliances and Inter-firm Knowledge Transfer", *Strategic Management Journal* 17, 77-91.

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

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

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

Powell, W. W. and S. Grodal (2005), *Networks of Innovators*. In: Fagerberg, J, Mowery, DC Nelson RR (Eds.), The Oxford Handbook of Innovation, Oxford University Press.

Rosenbaum, P. R. and D. B. Rubin (1983), "The Central Role of the Propensity Score Observational Studies for Causal Effects", *Biometrica* 70, 41-55.

Rothaermel, F. T. (2001), "Incumbent's Advantage Through Exploiting Complementary Assets via Interfirm Cooperation", *Strategic Management Journal* 22, 687–699.

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

Sakakibara, M. (1997), "Evaluating government-sponsored R&D consortia in Japan: who benefits and how?", *Research Policy* (26), 447-473.

Sakakibara, M. (2001), "The Diversity of R&D Consortia and Firm Behavior: Evidence from Japanese Data", *The Journal of Industrial Economics* 2, 181-196.

Schneider, C. and R. Veugelers (2010), "On young highly innovative companies: why they matter and how (not) to policy support them", *Industrial and Corporate Change, Oxford University Press* 19(4), 969-1007.

Smith, J. A. and P. E. Todd (2005), "Does matching overcome LaLonde's critique of nonexperimental estimators?", *Journal of Econometrics* 125, 305-353.

Smith, R. J. and R. W. Blundell, (1986), "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply", *Econometrica* 54, 679–685.

Sofka, W. and T. Schmidt (2009), "Liability of Foreignness as a Barrier to Knowledge Spillovers: Lost in Translation?", *Journal of International Management*, 15 (4), 460-474.

Solow, R. (1957), "Technical Change and the Aggregate Production Function", *Review of Economics and Statistics* 39, 312-320.

Suzumura, K. (1992), "Co-operative and noncooperative R&D in oligopoly with spillovers", *American Economic Review* 82, 1307-1320.

Teece, D. J. (1992), "Competition, Cooperation, and Innovation: Organizational Arrangements for Regimes of Rapid Technological Progress", *Journal of Economic Behavior and Organization* 18(1), 1-25.

Van Leeuwen, G. (2002), "Linking Innovation to Productivity Growth Using Two Waves of the Community Innovation Survey", *OECD Science, Technology and Industry Working Papers*, 2002/08, OECD Publishing.

Vonortas, N. (1994), "Inter-firm co-operation in imperfectly appropriable research", *International Journal of Industrial Organization* 12, 413-435.

Veugelers, R. (1998), "Technological collaboration: an assessment of theoretical and empirical findings", *De Economist* (149), 419-443.

Wooldridge J. M. (2002), *Econometric Analysis of cross section and panel data*, MIT Press.

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 ε. More precisely, $\|Zj – Zi\| < \varepsilon$ 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	0.30	0.36	0.11
2	Textiles, clothing and leather	87	4.41	0.56	0.47	0.51	0.21
3	Chemicals (incl. pharma), rubber / plastics	199	10.09	0.65	0.53	0.55	0.21
4	Metal	170	8.62	0.49	0.34	0.43	0.21
5	Machinery and vehicles	218	11.05	0.51	0.42	0.43	0.22
6	Electronics, communication and instruments	140	7.10	0.59	0.42	0.53	0.31
7	Other manufacturing industries	410	20.78	0.39	0.21	0.31	0.06
8	Trade	259	13.13	0.39	0.23	0.29	0.04
9	ICT services	177	8.97	0.47	0.31	0.40	0.14
10	Other business services	152	7.70	0.44	0.26	0.39	0.24
		1,973	**100.00**				

Table A.3: Size distribution

Size classes		Freq.	in %	*CO*	*CO_INTERNATIONAL*	*CO_NATIONAL*	IWT-subsidy
1	< 20 empl.	42	2.13	0.35	0.26	0.48	0.19
2	≥ 20 empl. & < 50 empl.	137	6.94	0.40	0.20	0.28	0.16
3	≥ 50 empl. & < 100 empl	872	44.2	0.41	0.21	0.31	0.11
4	≥ 100 empl. & < 250 empl.	595	30.16	0.61	0.35	0.40	0.14
5	≥ 250 empl.	327	16.57	0.75	0.64	0.66	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*	0.147	0.354	0	1
CO_INTERNAT	*dummy*	0.336	0.472	0	1
thereof					
EU_PARTNER	*dummy*	0.932	0.352	0	1
RoW_PARTNER	*dummy*	0.213	0.410	0	1
US_PARTNER	*dummy*	0.366	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*	0.753	0.413	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. Although one might be concerned about serial correlation when using lagged subsidies, rendering them not truly exogenous to the system of equations, our instruments fulfil the statistical requirements for instrumental variables. 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 thsd. EUR” 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). Moreover, our estimations take into account a possible correlation of error terms within repeated observation of the same firms by computing clustered standard errors at the firm level. The results of the IV regression are presented in Table A.5.

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)	0.094 ***		
	(0.036)		
SUBS		14.291 ***	7.053 ***
		(3.312)	(2.558)
INTCOOP_industry	0.086 ***	1.318	0.392
	(0.032)	(0.908)	(0.652)
*PS/EMP*1000*	2.878 ***	33.743	50.223
	(0.550)	(22.366)	(18.037)
ln(AGE)	-0.011	-0.073	-0.285
	(0.010)	(0.235)	(0.191)
ln(EMP)	-0.058 **	0.613	3.498
	(0.028)	(0.853)	(0.725)
ln(EMP)2	0.010 ***	-0.151	-0.297
	(0.003)	(0.100)	(0.069)
GROUP	0.024	0.756	0.255
	(0.020)	(0.620)	(0.419)
ln(LABPRO)	0.002	-1.330 ***	-1.122 ***
	(0.010)	(0.437)	(0.262)
FOREIGN	-0.078 ***	2.163 ***	0.261
	(0.023)	(0.820)	(0.386)
EXPORT	0.051 ***	0.566	1.965 ***
	(0.020)	(0.607)	(0.541)
R2 / Log-Likelihood	0.332	0.189	-4,709.168
F-Test of excl. instruments	F(2, 1592) = 12.33	-	-
Hansen's J test statistic	$\chi^2(1)$ p = 0.2445	-	-
Joint sign. of time dummies	7.50***	16.18***	39.06***
Joint sign. of ind. dummies	5.30***	88.96***	53.65***
Joint sign. of ind. dummies and size classes in heteroscedasticity term	-	-	237.85***

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%).

Appendix 3: Testing for potential endogeneity of international collaboration

We address the concern that international collaboration might be endogenous in the regressions on sales share from market novelties, by employing structural equation estimation as introduced by Smith and Blundell (1986). 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. Given that international collaboration is more cumbersome than national collaboration, past experience might play a more important role for international rather than for national collaboration. We also tested for the validity of our instruments, that is, 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 A6.[20] The first stage residual are insignificant in the second stage rejecting an endogeneity of both collaboration variables.

[20] Note that as an additional robustness check, we implemented an IV estimation as a Full Information Maximum Likelihood estimator with bootstrapped standard errors, where two equations are estimated simultaneously (see Wooldridge 2002: 530-533). Our findings remained unchanged.

Table A.6: 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)	4.223 ***		
	0.384		
IND_CONAT (IV_2)	3.780 ***		
	0.417		
PC_COINT (IV_3)		2.530 ***	
		0.504	
YEXPINT (IV_4)		3.201 ***	
		0.254	
ln(AGE)	-0.430 *	0.225	-6.167 **
	0.249	0.353	2.744
ln(AGE)2	0.076 *	-0.033	1.037 **
	0.040	0.054	0.422
ln(EMP)	0.014	-0.189	-3.968 **
	0.140	0.158	1.709
ln(EMP)2	-0.012	0.015	0.398 **
	0.015	0.018	0.178
RDINT	-0.010	-0.002	0.471 ***
	0.006	0.005	0.125
CO_INTERNATIONAL			5.482 ***
			1.580
CO_NATIONAL			0.779
			3.824
1st stage resid. *NATIONAL*			0.446
			1.734
1st stage resid. *INTERNAT*			-0.782
			1.101

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%).

CEPS
INSTEAD

3, avenue de la Fonte
L-4364 Esch-sur-Alzette
Tél.: +352 58.58.55-801
www.ceps.lu