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The virtue of industry-science collaborations

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ABSTRACT

This article analyzes the potential benefits of industry-science collaborations for samples of Flemish and German firms. A firm collaborating with science may benefit from knowledge spillovers and public subsidies as industry-science collaborations are often granted preferred treatment. I shed light on the potential spillover and subsidy effects by estimating treatment effect models using nearest neighbour matching techniques. For both countries, I find positive effects on business R&D. Firms that engage in industry-science collaborations invest more in R&D compared to the counterfactual situation where they would not collaborate with science. Furthermore, within the sample of firms collaborating with science, a subsidy for that collaboration leads, on average, to higher R&D in the involved firms. Thus there is no full crowding-out of subsidies targeted to science-industry collaborations.

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The virtue of industry-science collaborations

1. Introduction

The successful creation of new knowledge often depends on the ability of firms to establish collaborative R&D agreements in order to combine their resources, exploit complementary know-how, and internalize R&D externalities (Katz 1986; d'Aspremont and Jacquemin 1988; Kamien *et al.* 1992).

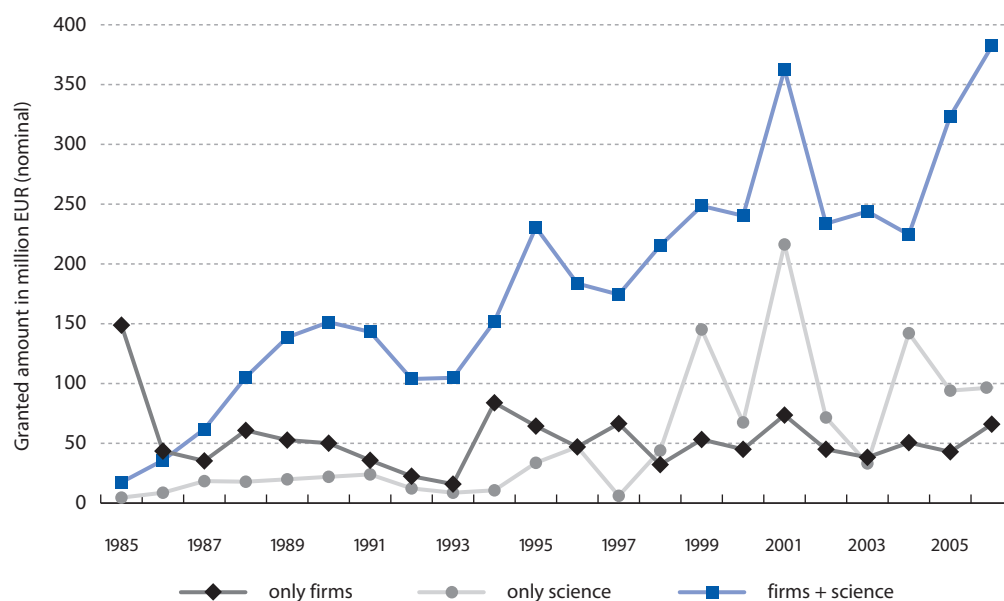
Governments have long understood the virtues of R&D collaboration and have exempted R&D partnerships from anti-trust legislation. In the European Union, for instance, the Treaty of Rome already contained a notice in article 85(3) that collaborating in R&D is permitted as long as post-innovation rivalry is not blocked. In 1984, the European Commission approved a block exemption for R&D collaborations that also allows joint exploitation of results (see Martin 1997 for an overview on policy practices in the US, Japan and Europe).

In addition, governments often subsidize R&D collaborations. Governments of EU member states often maintain subsidy schemes whereby grant applications from consortia are preferred over single-firm applications. In the recent past, technology transfer from science to industry has attracted the attention of policy makers and, as a result, industry-science collaborations are often granted a preferential treatment in public grant systems. It is believed that an enhanced knowledge and technology transfer from science to industry also contributes to the long-run innovativeness and thus competitiveness of the business sector. Figure 1 shows the development of grants from the German federal government to research consortia. It becomes apparent that, over time, industry-science partnerships were increasingly preferred in grant schemes when compared to pure company consortia or pure public science consortia.



Dirk Czarnitzki

Figure 1: Division of collaborative research grants by type of research consortia in Germany



Source: PROFI database from Germany's Federal Ministry of Education and Research; own calculations

**R&D collaborations
can help to internalize
spillovers and to exploit
synergies and scale
economies.**

The potential benefits of R&D collaborations can be summarized as follows. First, technological spillovers are internalized, thus eliminating the free-rider problem within the group of collaborating firms. Second, since R&D often exhibits economies of scale it might well be that only a consortium of firms has the necessary resources both financially and physically to undertake the ever larger, more complex, and more expensive research projects that are common today. Third, economies of scope also often characterize the R&D process. Hence, synergetic effects and risk pooling can broaden the research horizon of collaborating firms. It can thus be expected that sustaining R&D collaborations leads to an increase in private R&D activity. From the growing literature on R&D collaboration, it can be concluded that collaborative R&D levels exceed non-collaborative levels when technological spillovers are large, while the opposite holds for small technological spillovers (see Veugelers 1998 for a survey of the theoretical and empirical literature).

This study discusses the potential impacts of R&D subsidies to consortia of firms and public research institutions. It can be assumed that such collaborations are undertaken for projects where the research conducted concerns more basic and generic knowledge that may be difficult to be discovered by a single firm and may also lead to results that are more difficult to appropriate than those of more regular R&D conducted in the firm. First, I discuss the potential market failures in R&D and the economics of R&D collaborations, reviewing both the theoretical and the empirical literature. Second, I give a brief overview of the recent literature on effects of R&D policies at the firm level. The third goal of the study is the combination of both strands of literature which leads to an empirical study on how R&D subsidies to industry-science partnerships influence private R&D at the firm level.

2. Theory

2.1 The market failure for R&D investment

The standard argument for governmental intervention in the market for R&D is based on two market failure arguments. First, R&D creates positive external effects, that is, R&D creates knowledge and as Arrow (1962) hypothesized, something intangible such as knowledge cannot be kept fully secret by the original R&D investor. This implies that a private company investing in R&D will not be able to appropriate all returns on its initial investment as knowledge will spill over to rivals and other third parties that subsequently free-ride, *i.e.* build on the knowledge, without having participated in the investment. This may happen through the mobility of personnel, but also through many other channels such as joint customers or suppliers (see *e.g.* Mansfield 1985). Thus the social benefit of R&D investment is typically larger than the private return. As, however, firms only embark on investment with a positive expected private return, many R&D projects that are socially desirable may not be undertaken. This leads to a gap between social and private equilibrium and, consequently, a justification for government intervention.

The second market failure argument is typically established with respect to financing constraints for R&D. If a firm seeks external financial resources for an investment, R&D features several characteristics that make it more difficult or expensive to finance externally than, for instance, investment in tangible assets. For instance, the lion's share of an R&D investment project is sunk cost, as R&D mainly consists of wages for researchers. In contrast to physical capital investment, R&D itself cannot be used as collateral in credit negotiations with banks. Furthermore, the outcome of an R&D project is typically much more uncertain than the return on investment in physical capital, which also makes financiers less likely to invest (see *e.g.* Hall 2002 or Hall and Lerner 2009 for surveys of this strand of the literature).

Although these are good economic reasons for governments to support R&D by financing R&D in universities and also in the form of grants or tax credits to private companies, it is not straightforward to establish a clear-cut theoretical market failure argument for a preferential treatment of industry-science collaborations within certain schemes. Exempting R&D collaboration from anti-trust legislation can already be seen as a policy itself, as the possibility of collaborating in R&D (i) allows firms to internalize the potential external effects at least within the consortium of project partners, (ii) spreads the risk of outcome uncertainty and (iii) divides the cost of R&D among involved agents.

However, in combination with some empirical evidence from the literature on knowledge and technology transfer between science and industry, arguments for such extra incentives may be made.

It seems to be a generally accepted opinion that the involvement of universities or other public research institutions concerns more basic research projects and the transfer of more generic knowledge than the “usual” business R&D projects. The idea is that companies seek university collaboration for more fundamental, long-term and possibly strategic R&D projects. Empirical evidence supports this view (e.g. Hall *et al.* 2003; Belderbos *et al.* 2006). Thus, it could be argued that R&D conducted within industry-science collaborations involves projects that are socially more desirable than others, as more basic knowledge is created which expectedly would lead to higher knowledge spillovers, *i.e.* the social return on these investments is high. From the company perspective, however, basic research suffers from worse appropriability conditions than other projects. For instance, without any specific industrial application in mind, the original investor may not be able to take out a patent to protect the results of the initial investment.

Companies seek university collaboration for longer-term, more fundamental research whose results are more difficult to appropriate.

In addition, the uncertainty about expected pay-offs of such investments is typically even higher than for other R&D investment, as projects of more basic research are further away from the market and its potential applicability to new products and processes may be largely unknown at the time of investment. Thus, financial constraints may be more binding for basic research than for experimental development, for instance (see Czarnitzki and Hottenrott 2009; Czarnitzki *et al.* 2009).

This reasoning leads to the conclusion that the market failures due to external effects and financial constraints apply even more for research conducted within industry-science consortia than for other projects, justifying a higher degree of government intervention than for other R&D.

2.2 Theory of R&D collaboration

In the literature on policy evaluation, the standard question to be answered is “How much would a subsidized firm have invested in R&D if it had not been subsidized?” Econometric models are typically designed to estimate the potential “additional effect” of a subsidy with respect to its pure monetary value. As I will outline in the following, however, the evaluation of industry-science collaborations should include and separate two effects: first, the effect of the subsidy in terms of its additional capital that becomes available for investment of the recipient firm, and a possible effect on investment because of knowledge spillover effects between the collaborating parties. As the core of the industrial organization literature focuses on horizontal collaboration, that is, collaboration between competitors, I briefly outline the main aspects of this literature, and then turn to the differences in vertical and diagonal collaborations, *i.e.* collaborations with customers, suppliers and finally universities.

Horizontal collaboration

The question of how and why firms engage in R&D collaborations and how that affects welfare emerged during the 1980s in the economic literature (see Veugelers 1998 for a survey). The industrial organization literature emphasizes the importance of knowledge spillovers in the context of collaborative research (e.g. Katz 1986; d'Aspremont and Jacquemin 1988; Beath *et al.* 1988; De Bondt and Veugelers 1991; Kamien *et al.* 1992; Motta 1992; Suzumura 1992; Vonortas 1994; Leahy and Neary 1997). Such studies relate decisions to collaborate in R&D to the presence of spillovers and the effects on market performance with respect to profits. Models rely on the fact that returns from R&D are not fully appropriable by the firm, but knowledge leaks out to competitors such that social returns are higher than private returns. This leads to underinvestment in innovative activities from a social point of view. R&D collaborations are one possibility to internalize such knowledge spillovers and thus increase the appropriability of returns within research consortia. Three main issues with respect to collaborative R&D are considered in the following: coordination, free-riding and information sharing.

Investment in collaborative R&D increases with the level of knowledge spillovers.

Coordination in such models is typically described through joint profit maximization. One finding is that investment in R&D among collaborators increases with the level of spillovers. A second result states that if spillovers are high enough, that is, above some critical level, collaborating in R&D will result in higher investment compared to the status of no collaboration (see De Bondt and Veugelers 1991). As this will also lead to higher profits, firms have an increased incentive to engage in R&D collaborations in the presence of spillover effects. It should be noted, however, that the cost of coordinating R&D is often ignored in these models.

Collaborations bear the inherent risk of free-riding that may jeopardize the stability of the collaboration. Partners may free-ride as they could try to absorb knowledge from their partners but conceal their own (see e.g. Shapiro and Willig 1990; Baumol 1993; Kesteloot and Veugelers 1995). Models find that collaborative agreements for being profitable and stable require that involuntarily outgoing spillovers be not too high. This is in contrast with the results on coordination, where profits are higher with larger spillovers, regardless of their direction. Here the profitability of collaboration increases with the firms' ability to manage the outgoing spillovers in order to protect against the possible free-riding of partners.

Some models explicitly account for information sharing among partners, that is, for managing spillovers (e.g. Kamien *et al.* 1992, Katsoulacos and Ulph 1998). Katsoulacos and Ulph find that research joint ventures will always share at least as much information as non-collaborating firms because research joint ventures maximize joint profits. Another issue for managing spillovers is absorptive capacity. Cohen and Levinthal (1989) point out that incoming spillovers can be used more efficiently (in reducing own cost) when the firm is engaged in own R&D. Engaging in own R&D builds absorptive capacity, that is, the ability of a firm to benefit from the knowledge others have created through R&D activity. Kamien and Zang (2000) take that into account, and find ambiguous results of collaboration with respect to the level of firms' R&D investment. Yet, collaboration is still the more profitable option.

To conclude, theory states that non-collaborative R&D levels decrease with the magnitude of spillovers, while collaborative investment tends to increase with spillovers. Thus, imperfect appropriability of knowledge generating processes increases the benefits from collaborative agreements. The presence of spillovers increases the incentive for R&D collaboration as a means of internalizing this externality.

Theoretical results have initiated a debate on the implications of R&D collaborations for antitrust and the treatment of research joint ventures, leaving a favourable policy stance towards this type of collaboration (Ordober and Willig 1985; Jacquemin 1988; Shapiro and Willig 1990). Although it seems to be an important policy conclusion leading to more lenient policies towards R&D collaborations, it should be stressed that this only holds for co-operation restricted to R&D. If R&D collaboration facilitated product market collusion, the welfare enhancing results would not necessarily hold any longer.

Furthermore, it should be stressed that the vast majority of theoretical models deals only with horizontal R&D collaboration, that is, collaboration with competitors. While this set-up is predominant in theory, it stands in stark contrast to survey evidence: in practice, the most important partners are customers, suppliers and universities or other research institutions. By contrast, collaboration with competitors is not found to be frequent in R&D collaborations. This is a gap between theory and empirical “stylized facts”. Thus all interpretations with respect to linkages between economic theory and empirical results should be interpreted with care.

Vertical and diagonal R&D collaboration

As outlined above, the theoretical literature on vertical collaboration including industry-science collaboration is scarce. The economics of vertical R&D collaboration is different because vertical collaboration partners do not impose a negative externality on each other, as they do not compete in the same product market. Thus, the theoretical concerns about trade-offs in cost and benefits of R&D collaborations apply to a lesser extent to vertical collaboration. Firms may engage in vertical R&D collaboration to reduce the cost of R&D, e.g. a firm decides to collaborate with a university as the public research institution may possess superior knowledge for certain projects than the firm has internally available. Rather than generating this knowledge in-house, it may be preferable to seek it externally. Furthermore, seeking complementary knowledge may lead to economies of scale and scope which in turn result in increased in-house R&D (see Cassiman and Veugelers 2006).

Vertical R&D collaboration does not impose a negative externality on partners because they do not compete in the same product markets.

Similarly to horizontal collaboration, risk sharing arguments concerning the outcome uncertainty of R&D investment are a further motive for engaging in vertical collaboration. Firms would choose to engage in vertical collaboration if the expected benefits outweigh the transaction cost involved. Steurs (1995) is the first paper that extends models of R&D collaboration to inter-industry spillovers in a two-industry, two-firm-per-industry setting. It is assumed that intra-industry and inter-industry spillovers exist. As firms engaging in inter-industry collaboration do not impose a negative externality on each other, it is found that inter-industry collaboration is socially more beneficial than collaborations whose members come from a single industry. In the Steurs (1995) model, the industries are not related except for the presence of spillovers. This framework is extended by Inkmann (2000) who explicitly models strategic R&D investment in the presence of R&D spillovers between vertically related industries. The R&D investment of the upstream firm affects the production process or quality in the downstream firm which in turn leads to higher demand in the final product market and thus also for the intermediate good. In equilibrium, vertical collaboration maximizes the profits of the participating firms, and leads to increased R&D in the economy. A similar model is presented in Atallah (2002) where vertical R&D collaboration unambiguously leads to higher R&D and welfare in the economy. These papers are able to explain the empirical finding that vertical collaborations are more frequent than horizontal collaborations in reality. In addition, the paper by Steurs (1995) shows that “diagonal” collaboration is more beneficial than intra-industry collaboration. Industry-science collaborations could be seen as inter-industry collaborations as universities are not active in any market and thus neither horizontally nor vertically related to the firm in question.

3. Empirical evidence

This section first reviews a selection of empirical studies on the determinants of collaboration with special attention to industry-science partnerships and also reports some empirical evidence on the effects of these collaborations at the firm-level. Thereafter, results of empirical studies on the evaluation of R&D policies are briefly introduced. These two components then lead to studies that analyze both the effects of R&D policies and collaboration on firms' innovation activity.

3.1 Empirical studies on collaboration

Recent empirical studies have established that contractual forms of R&D, such as joint R&D, have become a very important mode of inter-firm and science-firm collaboration as the number of partnerships has largely increased (Sakakibara 1997; Hagedoorn and Narula 1996). Several empirical papers on R&D collaborations are reviewed in Veugelers (1998). As one recent example, Cassiman and Veugelers (2002) explore the effects of knowledge flows on R&D co-operation. Their results suggest that firms with higher incoming spillovers and better appropriability conditions have a higher probability of co-operating in R&D which confirms the arguments on spillovers made by theoretical contributions.

The role of universities may be a translation of basic science into an applicable technology.

Not many studies analyze industry-science collaborations explicitly. Hall *et al.* (2003) conduct a survey-based study of research projects having universities as research partners within the US ATP program. They argue that universities are involved in such projects that apply "new science", *i.e.*, firms seek for expertise to absorb results of basic research. The role of the university may be a translation of basic science towards an applicable technology for selected problems. This interpretation is supported by the fact that universities are engaged in industry collaboration in fields where business R&D is closer to science, particularly in areas where technology tends to be more complex. University involvement also occurs more frequently in projects that are broader in scope. Projects where results are expected in a timely manner for a specific technological problem are typically not conducted in collaboration with universities.

Veugelers and Cassiman (2005) explore the determinants of industry-science collaboration using Belgian Community Innovation Survey (CIS) data. They emphasize that there are large cross-industry differences in the probability of a firm collaborating with science. Firms in the chemical and pharmaceutical industry are most likely to collaborate with universities. Furthermore, firms that are impeded by high cost of innovation are often attracted by government subsidized cost-sharing in public-private partnerships. In addition, larger firms are more likely to collaborate with universities than smaller firms indicating that some minimum absorptive capacity is needed for fruitful collaboration. Moreover, it is often hypothesized that research projects involving a high uncertainty of outcome are preferably conducted within research consortia, as this allows to spread the risk. However, Veugelers and Cassiman find no evidence for the risk-sharing argument in industry-science collaborations with their data. The authors argue that the risk-sharing effect is possibly confounded with higher transaction cost when communicating with science. As long as these effects cannot be separately measured, results may remain ambiguous.

Belderbos *et al.* (2004a) also analyze the determinants of university collaboration. They account for collaborations with different types of partners by including a measure of incoming spillovers from these potential collaboration partners. Among others, one interesting finding is that spillovers received from universities not only stimulate industry-science partnerships but also R&D collaboration with other partners.

Belderbos *et al.* (2004b) investigate the impact of R&D collaboration on firm performance using panel data of Dutch manufacturing firms. The noteworthy feature of this study is the distinction of two dependent variables, growth of labour productivity and growth of firms' innovative sales, where the latter is measured as the growth rate in sales of products that were market novelties. Although these variables are treated as separate dependent variables not connected in a simultaneous-equation system, the results are interesting. It turns out that R&D collaborations with competitors and suppliers positively affect productivity growth. Belderbos *et al.* refer to this as a result of incremental innovation leading to higher sales of established products. In boosting innovative sales, however, university collaborations play an important role along with the collaboration with rivals. They also find that customers and universities are important sources of sales growth in market novelties even in the absence of formal collaborative agreements.

3.2 Empirical studies on R&D subsidies¹

The impact of R&D policies on firms' innovation behaviour has been of interest in the economic literature for decades. The predominant question investigated is whether public subsidies crowd-out private investment. David *et al.* (2000) survey microeconomic and macroeconomic studies on that topic. One result of their survey is that most of the estimations reviewed are subject to a potential selection bias as recipients of subsidies might be chosen by the government because they are the most promising candidates for successful research projects. In this case, public funding becomes endogenous to innovative activity, leading to bias in simple regressions of, for example R&D investment on government subsidies (selection bias).

More recent studies addressing the selection bias include Busom (2000), Wallsten (2000), Lach (2002), Czarnitzki and Fier (2002), Almus and Czarnitzki (2003), Duguet (2004), González *et al.* (2005) and Hussinger (2008). Results are ambiguous. Busom finds positive effects of public funding on R&D in Spanish manufacturing, but cannot rule out partial crowding-out for a sub-sample of firms. Wallsten finds full crowding-out effects in the US SBIR program, an initiative to foster innovation in small and medium-sized US companies. Lach reports large positive effects for small firms in Israeli manufacturing, but no effects for large firms. The analysis of Czarnitzki and Fier rejects full crowding-out effects in German service industries. Almus and Czarnitzki analyze East German manufacturing where the government has offered high amounts of subsidies in order to enhance the transformation process from central planning to a market economy since the German re-unification in 1990. They conclude that about 50 percent of R&D performed in East Germany would not have been carried out in the absence of public innovation programs. Duguet (2004) rejects crowding-out in R&D using a sample of French firms, as does Hussinger (2008) based on a sample of German firms using semi-parametric selection models. González *et al.* (2005) employ a large panel of Spanish manufacturing firms and find no evidence for crowding-out either.²

R&D subsidies tend to increase total R&D expenditure but often by less than the amount of the subsidy.

3.3 Studies combining collaboration and R&D subsidies

Just a few empirical analyses, however, deal with R&D co-operations as a part of firms' innovative behaviour *and* as a policy instrument. Among those, Sakakibara (2001) analyzes Japanese government-sponsored R&D consortia over 13 years and finds evidence that the diversity of a consortium is associated with greater R&D expenditure by participating firms. The results support the hypothesis of large spillover effects. The effect of participating in an R&D consortium on a firm's R&D expenditures is found

1 For an evaluation of another policy tool, the R&D tax credit, see Ientile and Mairesse (2009) in this issue.

2 Fewer studies deal with public policies and innovation outcomes such as growth of employment or sales. See the survey by Klette *et al.* (2000) for examples of such studies.

to be 9 percent on average. Branstetter and Sakakibara (2002) examine the impact of government-sponsored research consortia in Japan. They find evidence that participants of research consortia tend to increase their patenting after entering a consortium, which is interpreted as evidence for spillovers effects. The marginal increase of participants' patenting in targeted technologies, relative to the control firms, is large and statistically significant.

Czarnitzki and Fier (2003) employ econometric matching analysis to investigate the relationship between R&D collaboration and patent outcome as a measure of intermediate innovative output. Controlling for R&D input, firm size, industry heterogeneity and other common covariates, they find that firms that collaborate achieve higher patent outcomes than under no collaborative agreements. Using German data they also demonstrate that German R&D policy in the 1990s increasingly subsidized research consortia comprising firm-firm partnerships or industry-science partnerships. Czarnitzki and Fier find that firms in publicly-sponsored research consortia file more patents than other collaborators. However, they cannot disentangle whether this stems from more intensive science-industry interactions or simply from the R&D increase in response to the subsidy receipt.

Firms that both engage in R&D collaboration and receive R&D subsidies spend more on R&D than comparable firms with only one or none of these characteristics.

Czarnitzki *et al.* (2007) employ a heterogeneous treatment effects estimator where R&D collaboration, R&D subsidies and the combination of both are considered as a treatment. Their analysis is conducted for Community Innovation Survey data from Germany and Finland. Although the two countries have similar frameworks for technology policy, it can be observed that the frequency of R&D collaborations is much higher in Finland than in Germany in the early 2000s. Czarnitzki *et al.* (2007) find that both R&D collaboration and public R&D grants result in higher R&D in the treated firms. Firms that receive subsidies and are engaged in R&D collaboration exhibit complementarities in the sense that they invest more in R&D when benchmarked against each of the three following counterfactual situations: "only subsidy receipt", "only collaboration" and "neither subsidy receipt nor collaboration". This also points to the presence of sufficiently large spillovers in collaborative agreements, so that firms increase R&D inputs.

Another interesting result of Czarnitzki *et al.* (2007) is the analysis of "treatment effects on the untreated". As said above, the level of R&D collaboration is high in Finland. The econometric estimations show that firms not engaged in collaboration would not invest more in the counterfactual situation of engaging in R&D collaboration. In Germany, however, where R&D collaboration is less frequent, the authors find that firms would, on average, invest more in R&D if they did engage in collaboration. Thus, the authors conclude that there would be additional room for fostering collaboration in German technology policy while in Finland this seems to be limited. The Finish population of non-collaborating firms is to a larger extent characterized by very small firms, other than in Germany. Such firms may not have the necessary absorptive capacity or capabilities to benefit from R&D collaborations.

4. Econometrics: The evaluation question

To investigate the effect of public subsidies one has to construct the counterfactual situation: What would have been the behaviour of the subsidized firms had they not been subsidized? As the counterfactual cannot be observed it has to be estimated. Our fundamental evaluation question can be illustrated by an equation describing the average treatment effect on the treated firms. That is:

$$(1) \quad E(\alpha_{TT}) = E(Y^T|S=1) - E(Y^C|S=1)$$

where Y^T is the outcome variable. The status S refers to the group: $S=1$ is the treatment group and $S=0$ the non-treated firms. Y^C is the potential outcome which would have been realized if the treatment group ($S=1$) had not been treated. The problem is obvious. While the outcome of the treated individuals

What would have been the outcome of untreated firms if they had been treated?

in case of treatment, $E(Y^T|S=1)$, is directly observable, it is not the case for the counterfactual situation: What would these firms have realized if they had not received the treatment? $E(Y^C|S=1)$ is a counterfactual situation which is not observable and, therefore, has to be estimated.

The literature on the econometrics of evaluation offers different estimation strategies to correct for selection bias (see Heckman *et al.* 1999 or Imbens and Wooldridge 2009 for surveys). For cross-sectional data, popular choices for treatment-effect estimations are instrumental variable regressions, control function approaches (selection models) and matching estimators.

In this study, I employ a nearest-neighbour propensity score matching. The advantage of matching is that no parametric model for the R&D equation has to be specified. The counterfactual outcome of treated firms is constructed from a control group of non-treated firms. The matching relies on the intuitively attractive idea to balance the sample of program participants and comparable non-participants. Remaining differences in the outcome variable, *e.g.* R&D intensity, between both groups are then attributed to the treatment. Initially, the counterfactual situation cannot simply be estimated as the observed average outcome of the non-participants, because due to the possible selection bias, the subsidized firms and non-subsidized firms are expected to differ. Hence, $E(Y^C|S=1) \neq E(Y^C|S=0)$.

Rubin (1977) introduced the conditional independence assumption (CIA) to overcome the selection problem. The CIA states that participation and potential outcome are independent for firms with the same set of exogenous characteristics X . Phrased differently, the selection only occurs on observables:

$$(2) \quad Y^C \perp S \mid X$$

If this assumption is valid, it follows that

$$(3) \quad E(Y^C \mid S = 1, X) = E(Y^C \mid S = 0, X).$$

Equation (3) states that the outcome of the non-participants can be used to estimate the counterfactual outcome of the participants in case of non-participation, provided that there are no systematic differences between both groups. The treatment effect can be written as

$$(4) \quad E(a_{TT}) = E(Y^T|S=1, X=x) - E(Y^C|S=0, X=x)$$

Conditioning on X takes account of the selection bias due to observable differences between participants and non-participants. In nearest-Neighbour matching, one picks the most similar firm from the potential control group of non-subsidized firms. In addition to the CIA, another important precondition for consistency of the matching estimator is common support: it is necessary that the control group contains at least one sufficiently similar observation for each treated firm. In practice, the sample to be evaluated is restricted to common support. However, if the overlap between the samples is too small the matching estimator is not applicable.

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

5. Empirical study

For the first analysis, I employ data obtained from the Flemish Community Innovation Survey (CIS) 2005 and 2007, *i.e.*, the data refer to the years 2004 and 2006. In these surveys, respondents were requested to indicate whether they received public subsidies from the local, federal or European authorities. In addition, they were asked to specify if the subsidy was granted within a research consortium and whether that consortium included at least one public research institution. The latter will be defined as subsidized industry-science collaboration.

For a second analysis, I use data from the German CIS. Here, data from the surveys of the years 2001 and 2005 can be used, *i.e.*, the data refer to the years 2000 and 2004.³ Firms were also asked whether they received subsidies from the government. However, the information on whether the subsidized projects involved industry-science collaboration, too, needs to be collected separately from the PROFI database of the German Federal Ministry for Education and Research (BMBF) which covers all federally subsidized civilian R&D projects in Germany (BMBF 2009).

5.1 Data description

In total, the usable sample of the Flemish CIS comprises 3,331 firm-year observations of which 1,791 can be classified as innovators. An innovator is a firm that introduced at least one product or one process innovation in the past three years, or had ongoing or abandoned innovation projects. Thus, this constitutes the sub-population of firms that at least attempted to innovate.

Out of those innovating companies, 890 firms engaged in some type of collaborative agreement, of which 532 firms were involved with partners from public science (60 percent). Of the 532 firms with industry-science partnerships, 230 received public subsidies for the industry-science partnership (43 percent).

For Germany, the data are quite similar. 1,074 collaborating companies can be identified within the survey data. Out of those, 804 collaborate with public science (75 percent). Among those 804 observations, 284 received subsidies from the federal government (35 percent).

5.2 Set-up of econometric study and variables

For this study, we use the sub-sample of firms engaging in any type of collaborative agreement as a starting point, and investigate two research questions:

Do firms that collaborate with public science spend more on R&D than in the counterfactual situation where they would not?

Among firms collaborating with public science, do firms that receive subsidies spend more on R&D than in the counterfactual situation of not receiving subsidies?

For both research questions, I employ the nearest-neighbour matching technique described above. First, industry-science collaboration is interpreted as a “treatment” within the sample of collaborating firms. Subsequently, the subsidy receipt within the sample of industry-science partnerships is considered as a treatment.

³ Although the CIS is harmonized across countries, the questionnaires are not identical in each year and for all countries. In Flanders, the question on collaboration behavior is available for 2005 and 2007 while it was asked only in 2001 and 2005 in Germany. For a detailed description of the CIS see *e.g.* Eurostat (2008).

Do firms engaged in industry-science collaboration spend more on R&D than firms collaborating with other firms?

The dependent variable is R&D intensity (*RDINT*), measured as R&D spending divided by sales, times 100.

For the matching procedure, a relatively large set of control variables can be included. Firm size is measured in terms of employment (EMP). As the firm size distribution is skewed, the variable enters in logarithms. I also allow for a potential non-linear relationship by including $[\ln(\text{EMP})]^2$. Furthermore, the log of firms' age is considered, as younger firms might be relatively more innovative ($\ln(\text{AGE})$). Another important control is previous successful R&D activities. On the one hand, this may account for the absorptive capacity in the firm. On the other hand, it may approximate the attractiveness of a firm as a potential collaboration partner. I measure previous successful innovation by a dummy variable indicating whether the firm has filed at least one patent in the past. For the Flemish sample this takes into account patents filed with the European Patent Office (EPO) before the corresponding survey year. For Germany, this variable also accounts for patents filed with the German national patent office. In order to control for the degree of competition a company faces, I include an export dummy (EXPORT) that equals one if the firm is an exporter and zero otherwise, as firms in international markets may be forced to innovate more than others if they want to remain competitive in the global economy.

In addition, I use a dummy indicating whether the company is part of an enterprise group, such as a multinational company or a holding company (GROUP). It may imply more professional innovation management of the firm (especially when compared to small stand-alone companies). A further control variable indicates whether or not the parent company is located abroad (FOREIGN). Such firms may be less likely to receive local public funding. Last but not least, a set of industry dummies controls for unobserved heterogeneity across sectors and a time dummy captures common macroeconomic shocks.

Table 1 shows the means of all variables used for the different Flemish sub-samples. In the upper panel, it can be seen that firms engaged in industry-science partnerships show higher R&D intensity than other collaborators (6.3 percent *versus* 2 percent). However, the two groups also differ significantly with respect to export and patenting activities. Thus, the difference in R&D intensity cannot simply be assigned to the fact that firms engage in industry-science partnerships and receive spillovers that lead to higher investment.

In the lower panel of Table 1, the 532 firms with industry-science partnerships are split into those that received public subsidies for their projects and others. Similarly as above, firms that received subsidies show higher R&D intensity but they also differ in export and patenting activities. It remains to be investigated if the higher R&D input can be assigned to the subsidy.

The matching of treated with untreated firms is based on firms' size, age, R&D track record and competitive pressure.

Firms engaged in industry-science partnerships have higher R&D intensity than firm-firm collaborations but they differ with respect to other variables as well.

Table 1. Flemish data – Means of all variables by sub-sample

Sample 1: Firms that collaborate but not with public science versus firms that collaborate with public science			
	No industry-science partnership (358 obs.)	Industry-science partnerships (532 obs.)	t-test on mean differences
Ln(EMP)	4.20	4.34	
GROUP	0.62	0.67	*
FOREIGN	0.33	0.32	
DEX	0.79	0.86	***
Y2006	0.54	0.58	
Ln(AGE)	3.10	3.18	
PATENT	0.09	0.26	***
RDINT	2.00	6.30	***
Sample 2: Firms that collaborate with public science without subsidy receipt versus subsidy recipients			
	Non-subsidized industry-science partnerships (302 obs.)	Subsidized industry science partnerships (230 obs.)	t-test on mean differences
Ln(EMP)	4.31	4.39	
GROUP	0.70	0.63	*
FOREIGN	0.33	0.30	
DEX	0.90	0.84	*
Y2006	0.56	0.62	
Ln(AGE)	3.22	3.12	
PATENT	0.19	0.35	***
RDINT	3.65	9.76	***

Notes: *** (**, *) indicate a significance level of 1 percent (5 percent, 10 percent). Industry dummies omitted.

For the German sample, we also find differences between firms collaborating with public science and other collaborators. The former are on average larger, more active on export markets, and are more likely to have at least one patent. On average, their R&D intensity amounts to 8.8 percent, compared with 4.2 percent for the group of other collaborators (Table 2).

Within the group of German firms that collaborate with science, there are also significant differences between firms that receive a subsidy for the science collaboration and those that do not. Interestingly, on average, the subsidized firms are smaller and younger than the non-subsidized firms. They are nevertheless more likely to have a patent. With respect to R&D intensity, subsidized firms reach almost 13 percent and the non-subsidized firms roughly 7 percent.

Table 2. German data – Means of all variables by sub-sample

Sample 1: Firms that collaborate but not with public science versus firms that collaborate with public science			
	No industry-science partnership (270 obs.)	Industry-science partnerships (804 obs.)	t-test on mean differences
Ln(EMP)	4.45	4.78	***
GROUP	0.57	0.59	
FOREIGN	0.15	0.13	
DEX	0.65	0.76	***
Y2004	0.53	0.54	
Ln(AGE)	2.93	2.86	
PATENT	0.72	0.85	***
RDINT	4.21	8.78	***
Sample 2: Firms that collaborate with public science without subsidy receipt versus subsidy recipients			
	Non-subsidized industry- science partnerships (520 obs.)	Subsidized industry science partnerships (284 obs.)	t-test on mean differences
Ln(EMP)	4.93	4.52	***
GROUP	0.62	0.55	*
FOREIGN	0.13	0.14	
DEX	0.74	0.79	*
Y2004	0.53	0.55	
Ln(AGE)	2.93	2.73	***
PATENT	0.83	0.89	**
RDINT	6.65	12.69	***

Notes: *** (**, *) indicate a significance level of 1 percent (5 percent, 10 percent). Industry dummies omitted.

5.3 Matching

In this sub-section I report the results of the nearest-neighbour matching. First, it is investigated whether the differences in R&D intensity between firms that collaborate with science and other collaborators can be assigned to the fact of engaging in industry-science collaboration. Thus, for each firm in the sample of firms that collaborate with science, I pick the most similar firm from the control group, *i.e.* collaborating firms that chose not to involve public science in their research consortia. The R&D intensity of the drawn controls is used as an estimate for the counterfactual situation, that is, what the firms that collaborate with science would have invested if they had not collaborated with science.

To implement the nearest-neighbour matching, I require that the picked control operates in the same industry as the firm in question. Among those, the firm with the most similar propensity to collaborate is drawn as control (see Table A1 in the Annex for a detailed matching protocol). The propensity to collaborate with public science is determined by the estimation of probit models on the treatment indicator. Results of the probit models are presented in Tables A2 and A3 in the Annex.

Table 3 below presents the matching results for Flanders. Out of the 532 firms that collaborate with science, the matching algorithm succeeds in finding a twin firm for 500 observations. As one can see in the upper panel, the samples are now balanced in the covariates after the matching routine.

Firms engaged in subsidized industry-science collaborations spend more on R&D than non-subsidized R&D collaborators but other variables are different, too.

The treated group of firms does no longer differ significantly in its characteristics from the selected control group which can now be used as an estimate for the counterfactual situation.

For the first estimation, the treatment effect amounts to 3.1 percentage points of R&D intensity (5.87 – 2.77), and is significant at the 1-percent level. Thus, we conclude that firms engaging in industry-science collaborations increase their R&D spending as a response to this “treatment”, all else constant.

The treatment effects estimation for subsidized industry-science collaborations in Flanders is presented in the lower panel of Table 3. Now the group of firms collaborating with public science is split into those that receive subsidies for the public-private partnership and non-subsidized industry-science consortia. The controls for the subsidized firms are drawn as nearest neighbours from the sample of non-subsidized firms. For 222 out of the 230 initial observations, the matching algorithm could find an appropriate control. For this second estimation, the treatment effect is about 5.1 percentage points (9.4 – 4.3), and is also significant at the 1-percent level. Thus, we find that even within the sub-sample of firms engaging in industry-science partnerships, the public subsidy receipt triggers still higher R&D investment. Consequently, full crowding-out effects of the policy of funding research consortia with involvement of public science can be rejected in this setting, as the estimated treatment effect due to the subsidy (about 5 percentage points in terms of R&D intensity) is significantly larger than zero.

When controlling for differences in other variables, treatment effects are positive both for industry-science collaborations and subsidized industry-science collaborations in Flanders.

Table 3. Flemish data – matching results: Means of all variables by sub-sample for treated firms and selected controls

Sample 1: Firms that collaborate but not with public science versus firms that collaborate with public science			
	No industry-science partnership (500 obs.)	Industry-science partnerships (500 obs.)	t-test on mean differences
Ln(EMP)	4.03	4.27	
GROUP	0.62	0.67	
FOREIGN	0.29	0.32	
DEX	0.84	0.86	
Y2006	0.61	0.58	
Ln(AGE)	3.14	3.16	
PATENT	0.22	0.19	
RDINT	2.77	5.87	***
Sample 2: Firms that collaborate with public science without subsidy receipt versus subsidy recipients			
	Non-subsidized industry- science partnerships (222 obs.)	Subsidized industry science partnerships (222 obs.)	t-test on mean differences
Ln(EMP)	3.90	4.34	
GROUP	0.58	0.63	
FOREIGN	0.31	0.32	
DEX	0.92	0.89	
Y2006	0.66	0.62	
Ln(AGE)	3.14	3.13	
PATENT	0.27	0.34	
RDINT	4.33	9.44	***

Notes: *** (**, *) indicate a significance level of 1 percent (5 percent, 10 percent). Industry dummies omitted. Selected controls are active in the same industries as the treated firms.

For the German data, the results of the matching estimator are quite similar. The procedure is equivalent to that run on the Flemish data with the exception that the survey year needs to be added as a matching argument. Thus, the samples are here exactly balanced with respect to industry and year. Based on these restrictions, the most similar firm in terms of the propensity score is drawn as control group for the respective firm in the treatment group. In the sample of firms collaborating with science, the matching algorithm finds appropriate controls for 775 out of the initial 804 firms in the treatment sample. The estimated treatment effect of industry-science collaboration amounts to about 4 percentage points of R&D intensity (8.91 – 4.87), and is significant at the 1-percent level.

Among the industry-science collaborators, we can match 261 of the 284 firms that received a subsidy with appropriate controls, *i.e.* firms collaborating with science without being subsidized. Here, too, the treatment effect is of similar magnitude as in the Flemish sample. It amounts to about 3.7 percentage points (13.01 – 9.33) and is also significant at the 1-percent level.

Table 4. German data - matching results: Means of all variables by sub-sample for treated firms and selected controls

German firms have positive treatment effects, too.

Sample 1: Firms that collaborate but not with public science versus firms that collaborate with public science			
	No industry-science partnership (775 obs.)	Industry-science partnerships (775 obs.)	t-test on mean differences
Ln(EMP)	4.43	4.62	
GROUP	0.57	0.58	
FOREIGN	0.16	0.14	
DEX	0.77	0.75	
Y2004	0.55	0.55	
Ln(AGE)	2.79	2.85	
PATENT	0.85	0.85	
RDINT	4.87	8.91	***

Sample 2: Firms that collaborate with public science without subsidy receipt versus subsidy recipients			
	Non-subsidized industry- science partnerships (261 obs.)	Subsidized industry science partnerships (261 obs.)	t-test on mean differences
Ln(EMP)	4.65	4.57	
GROUP	0.54	0.56	
FOREIGN	0.17	0.13	
DEX	0.79	0.79	
Y2004	0.55	0.55	
Ln(AGE)	2.86	2.78	
PATENT	0.88	0.89	
RDINT	9.33	13.01	***

Notes: *** (**, *) indicate a significance level of 1 percent (5 percent, 10 percent). Industry dummies omitted. Selected controls are active in the same industries as the treated firms and refer to the same year.

Therefore, we can conclude that subsidizing industry-science partnerships does not appear to be subject to full crowding-out effects in either Germany or Flanders.

Treatment effects would not necessarily remain as strong if the schemes were extended to additional firms.

It should be noted, however, that it is not possible to conclude that an expansion of such policy schemes would lead to higher R&D in the economy. The treatment effects estimation only allows evaluating the program effect for the firms that were actually treated. An expansion of such a policy may lead to entry of firms that show significantly different characteristics from the currently treated firms. Thus, it may happen that treatment effects would get smaller if firms that newly enter the schemes lack the necessary absorptive capacity to benefit from scientific knowledge or are in a different financial situation so that they are not able to raise additional capital for further R&D (even in the presence of a subsidy) and thus cause higher crowding-out effects of the scheme. Consequently, the analysis above is only able to report positive treatment effects for the *status quo* but these findings cannot be used as *ex-ante* evaluations of changes in the schemes.

As a robustness check, I finally control for heterogeneous collaboration patterns of the firms in the sample. Firms may either collaborate horizontally, vertically or in both directions over and above their collaboration with public science. Consequently, I perform analyses equivalent to those above but include dummies for the other collaboration patterns as a matching argument. Thus, the drawn controls are active in the same industry, are most similar in the control variables as used above and also show the same collaboration pattern with respect to vertical and horizontal collaboration as the treated firms. As the results are virtually the same as above I do not present them here.

6. Conclusions

This study has shown an example for the evaluation of industry-science R&D collaborations. Industry-science partnerships may influence the R&D activities of the involved business partners. As outlined, theories of industrial organization suggest that R&D collaborations may lead to higher R&D because firms can internalize potential external effects of R&D, that is, free-riding of other firms due to knowledge spillovers. Furthermore, it has been described that collaborations with universities or other public research institutions may lead to higher R&D than collaborations with horizontally related firms as the former do not exert a negative externality on profitability since universities are not involved in any market rivalry with the firm.

In addition to the potential knowledge spillover effect, business R&D may be influenced by subsidies. Granting subsidies to research consortia rather than individual firms is currently a popular policy, and among the former, industry-science partnerships receive preferential treatment in many EU member states. Thus, firms may benefit in two ways from the collaboration with science. First, they may benefit from knowledge spillovers and second, public subsidies lower the price of R&D conducted in the firm.

As an example for possible evaluations of the benefits of industry-science collaborations I employ nearest-neighbour matching techniques to firm level data from Germany and Flanders. First, treatment effects of R&D collaboration with public science are estimated using comparable firms that collaborate in R&D, but not with public science, as a control group. Second, the firms that collaborate with public science are split into those that engage in subsidized industry-science consortia and those that collaborate with public science without being subsidized. For both scenarios, I find positive treatment effects, and can thus reject full crowding-out effects of policy schemes supporting industry-science collaborations.

It should be noted, however, that the analysis cannot tell whether an expansion of such policies would lead to similar treatment effects. In the extreme case, all companies that could potentially benefit from collaborating with science may actually do so already. New entrants into a policy scheme for (subsidized)

science-industry collaboration may not show an increase in R&D as they, for instance, may lack the necessary absorptive capacity. Thus, the results of the treatment effects analysis can only shed light on actual program participants. The findings cannot be extrapolated to a hypothetical situation with more participating firms.

In addition, industry-science collaborations may not be unambiguously welfare-enhancing. If it is believed that the primary task of university research is basic science and that results of basic science lead to higher welfare in the long run, one may ask whether basic research suffers from industry-science collaboration in the long term. Increased commercialization of university research may distract researchers from their basic research tasks. This assumption is not implausible as a firm typically seeks specific solutions for technological problems emerging in its business. Thus, engaging in industry-science collaborations may force university researchers to shift their attention to more applied research questions that possibly have to be addressed within tight deadlines. Basic research output might suffer under these circumstances. Czarnitzki *et al.* (2009) analyze this question using individual data of German professors. They correlate their publication counts and quality with patenting activity where patents are differentiated into purely academic patents and corporate patents. The latter are patents where the university researcher appears as the inventor and a firm as the patent applicant. This can be interpreted as an indicator for an engagement in industry-science collaboration. Regression analysis shows that such collaboration harms the publication output of the scientist with respect to both quantity and quality whereas commercialization activity measured as academic patenting does not. Lower(-quality) publication output may be an indication of the opportunity cost of science-to-industry technology-transfer policies, especially if additional subsidies to industry-science collaborations are financed by reductions in basic public university budgets – a trend that can be observed for Germany.⁴ The potential benefits in business R&D should therefore be carefully assessed against potentially negative effects occurring in knowledge output of public science.

The benefit of industry-science collaboration for business R&D should be carefully balanced against the opportunity cost in terms of lower academic publication output.

⁴ Between 1981 and 2005, German higher education R&D expenses remained more or less constant at 0.4 percent of GDP. During the same time, however, the share of higher education R&D financed by the business sector grew from 2 percent to 14 percent (OECD 2009).

Annex: Matching protocol and probit estimations

The following matching protocol summarizes the empirical implementation of the nearest neighbour matching procedure used in this study.

Table A1. The matching protocol

Step 1	Specify and estimate a probit model of engaging in industry-science collaboration and receiving a subsidy, respectively, to obtain the propensity scores $\hat{P}(X)$.
Step 2	Restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. In this study, I apply the common support restriction for each industry separately, as it is required that the treated firms and selected controls belong to the same industry (see Step 5).
Step 3	Choose one observation from the sub-sample of treated firms and delete it from that pool.
Step 4	Calculate the distance between this firm and each non-subsidized firm in order to find the most similar control observation. As we match on the propensity score, we use a Euclidian distance. (In case multiple matching arguments are used a standard choice is the computation of a Mahalanobis distance. This has been done for the robustness check where hybrid matching has been used.)
Step 5	Select the observation with the minimum distance from the remaining sample. In this study, I restrict the potential control group to firms that are active in the same industry as the treated firm in question. (Do not remove the selected controls from the pool of potential controls, so that it can be used again.)
Step 6	Repeat Steps 3 to 5 for all observations on subsidized firms.
Step 7	Using the matched comparison group, the average effect on the treated can thus be calculated as the mean difference of the matched samples: $\hat{\alpha}_{\pi} = \frac{1}{n^T} \left(\sum_i Y_i^T - \sum_i Y_i^C \right)$ with Y_i^C being the counterfactual for firm i and n^T the sample size (of treated firms). Note that the same observation for Y_i^C may appear more than once in that group.
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 for valid statistical inference. We follow Lechner (2001) and calculate his estimator for an asymptotic approximation of the standard errors.

Tables A2 and A3 present the propensity score estimation for the Flemish and German samples. The propensity scores are used to pick the most similar control observation within the matching procedure.

Table A2. Flemish data: Probit regressions on treatment dummies

Variable	SAMPLE 1	SAMPLE 2
LnEMP	-0.689*** (0.128)	-0.507*** (0.134)
(LnEMP) ²	0.076*** (0.014)	0.062*** (0.014)
GROUP	0.296** (0.117)	-0.228 (0.158)
FOREIGN	-0.169 (0.116)	-0.061 (0.146)
Y2006	0.088 (0.092)	0.199* (0.121)
EXPORT	0.221* (0.126)	0.279 (0.184)
LnAGE	0.072 (0.054)	-0.062 (0.077)
PATENT	0.646*** (0.133)	0.451*** (0.141)
Intercept	0.868** (0.348)	0.435 (0.425)
Industry dummies	YES	YES
McFadden R ²	0.09	0.11

Note: Standard errors in parentheses. *** (**, *) indicate a significance level of 1 percent (5 percent, 10 percent).

Table A3. German data: Probit regressions on treatment dummies

Variable	SAMPLE 1	SAMPLE 2
LnEMP	-0.092 (0.118)	-0.117 (0.110)
(LnEMP) ²	0.019* (0.011)	0.007 (0.009)
GROUP	-0.081 (0.105)	-0.141 (0.116)
FOREIGN	-0.177 (0.136)	0.228 (0.150)
Y2004	-0.196* (0.109)	-0.037 (0.109)
EXPORT	0.177* (0.110)	0.347*** (0.125)
LnAGE	-0.127*** (0.054)	-0.049 (0.059)
PATENT	0.530*** (0.135)	0.438*** (0.159)
Intercept	0.615 (0.386)	-0.597 (0.434)
Industry dummies	YES	YES
McFadden R ²	0.07	0.07

Note: Standard errors in parentheses. *** (**, *) indicate a significance level of 1 percent (5 percent, 10 percent).

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