Discussion Paper No. 04-37

The Relationship between R&D Collaboration, Subsidies and Patenting Activity: Empirical Evidence from Finland and Germany

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Non-technical summary

In 2002 the European Council Member States decided to intensify their activities to increase investment in research and technology development to close the enlarging gap with Europe's main "competitors", the United States and Japan. The aim was to raise investments in research from 1.9% to 3.0% of GDP in the European Union by 2010 ("Action Plan 2010"), where the share spent by the business sector should rise by two-thirds of the total. Meeting the "3% goal" depends on some crucial relationships. It is assumed by the national governments that public incentives for R&D actually foster private activities. This relationship is by no means clear, as every firm has an incentive to apply for public grants and substitute private investment for public investment. Also, the emphasis on collaborative research in recent policies does not necessarily lead to more innovation.

In this paper we analyze the relationship between public R&D funding, R&D collaborations and innovative output with a sample of German and Finnish firms. In particular, we conduct a treatment effects analysis on the impact of public incentives and collaboration on patenting activities, where we interpret collaboration, public funding and a combination of both as "treatments". Positive relationships between those treatments and the innovative outcome are necessary prerequisites for the success of the European Governments' Action Plan in order to secure long-term growth and employment.

A comparison between Germany and Finland seems to be a reasonable choice, because Germany is the largest economy in the EU and has shown only average innovative performance recently and Finland is the "shooting star" among the rising smaller European countries. Finland's fundamental structural shift from a resource-based economy to a knowledge-based economy is the leading-the-way example among European countries.

The analysis is based on the second and third waves of the Community Innovation Survey for Germany and Finland, covering the time from 1994 to 1996 and 1998 to 2000, and containing 1,464 (1,520) German (Finnish) companies with innovative activities. We employ a nearest-neighbour matching as well as a quasi difference-in-difference approach to estimate the impacts of collaboration for innovation, public funding and both.

Our results show that in Finland R&D collaboration and R&D subsidies yield positive treatment effects in the groups actually receiving such treatment, compared with the situation in the absence of treatments; in Germany we cannot support this hypothesis for firms that receive R&D subsidies for individual research. In addition, we find a large innovation potential in the group of non-treated firms that could be utilized by collaboration in Germany but is currently not exploited; in Finland this effect is substantially smaller, possibly due to the high share of firms already engaged in collaboration. A larger proportion of the remaining firms may not maintain enough capabilities to benefit from collaboration.

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Dirk Czarnitzki*, Bernd Ebersberger** and Andreas Fier***

This Version: January 2006

Abstract

This study focuses on the impact of innovation policies and R&D collaboration in Germany and Finland. We consider collaboration and subsidies as heterogeneous treatments, and perform an econometric matching to analyze R&D and patent activity at the firm level. In general, we find that collaboration has positive effects. In Germany, subsidies for individual research do not exhibit a significant impact neither on R&D nor patenting, but the innovative performance could be improved by additional incentives for collaboration. For Finnish companies, public funding is an important source of finance for R&D. Without subsidies, recipients would show less R&D and patenting activity, whilst those firms not receiving subsidies would perform significantly better if they were publicly funded.

Keywords: R&D, Public Subsidies, Collaboration, Policy Evaluation

JEL-Classification: C14, C25, H50, O38

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The authors are grateful to Statistics Finland for making available the Finnish data. The financial support by the Finnish National Technology Agency of Finland (Tekes) and the Finnish Ministry of Trade and Industry is gratefully acknowledged. We thank Bruno Cassiman, Bernd Fitzenberger, Heinz Hollenstein, Guido W. Imbens, Jordi Jaumandreu, Michael Lechner, Jacques Mairesse, Pierre Mohnen as well as the editor and two anonymous referees for helpful comments. The paper also benefited from comments by the audience at following conferences and seminars: International Industrial Organization Conference, Chicago; Applied Econometrics Association, Singapore; Rutgers University, NJ; 15th EC2 Conference, Marseille; University of Dortmund; Statistics Iceland, Reykjavík; Austrian Research Centers, Austria.

1 Introduction

All over the OECD countries business strategies for R&D and innovation have evolved significantly in industry and governments during the past decades. Considerable evidence indicates an increasing number of R&D co-operations, mergers and patent licences, and alliances in industry and science. Innovation policy shifted from the focus on big science carried out by large companies only to a general trend towards R&D networking and intensified efforts to strengthen domestic firms, technologies and competencies.

The European Council Member States decided to intensify their activities to increase investment in research and technology development to close the enlarging gap with Europe’s main "competitors", the United States and Japan. The gap in research investment between the European Union and the United States is already in excess of EUR 120 billion per year and widening, with alarming consequences for the long-term potential for innovation, growth and employment creation in Europe. For this reason, the European Council decided to make every effort to raise investments in research from 1.9% to 3.0% of GDP in the European Union by 2010 ("Action Plan 2010"), where the share spent by the business sector should rise by two-thirds of the total (European Commission, 2003).

For achieving this aim, European governments use different mixes of innovation policy instruments. These instruments are implemented to foster public R&D and to stimulate private business R&D expenditures often justified by market failures. Externalities and information asymmetries are commonly recognized as the most important market failures hampering R&D investment (see e.g. Hall, 2002). Due to these market failures, and for reasons of competitiveness, governments employ policy tools like patent laws, R&D grants, low interest loans or tax incentives to strengthen national R&D activities.

In 2001 different public innovation policies accounted for 0.76% in the USA, 0.67% in the total OECD and 0.66% in the European Union as a percentage of Government-financed R&D expenditure (GERD) relative to GDP. Due to this gap in public investments in R&D, and because of decreasing European national budgets, governments are forced to identify the most efficient allocation of public money. Thus direct subsidies for collaborative research have become a favoured incentive scheme in European countries. For example, in Germany the Federal Government funded about 100 collaborative research projects in industry in 1980. In 1990 this figure was already about 2,100 and rose to more than 7,500 funded collaborative research projects in 2001 (see Czarnitzki and Fier, 2003). On the one hand, collaborations are a possibility to internalize the positive external effects occurring in the creation of knowledge, and thus to improve the appropriability of research results within the consortium of project partners. On the other hand, positive spillovers among collaborating firms, as well as cost and risk sharing on both the government's and the companies' sides, are expected. In contrast, however, the is a risk that firms use R&D collaborative agreements to collude also in the product market. This could harm welfare.

Meeting the "3% goal" as aimed at by the European Council's "Action Plan 2010" depends on some crucial relationships: it is assumed by the national governments that public incentives for R&D actually foster private activities. This relationship is by no means clear, as every firm has an incentive to apply for public grants and substitute private investment for public investment. On the other hand, the emphasis on collaborative research in recent policies does not necessarily lead to more innovation. Collaboration in R&D could result in higher transaction costs and it may be possible that firms with the most promising research plans are reluctant to collaborate because their knowledge leaks out to all collaboration partners. If secrecy is preferred, they may not apply for subsidies. In the worst case, promising future technologies might not be developed due to a lack of alternative sources of finance.

In this paper we analyze the relationship between public R&D funding, R&D collaborations and innovation effort and subsequent innovation output with a sample of German and Finnish firms. In particular, we conduct a treatment effects analysis on the impact of public incentives and collaboration on R&D and patenting activities. Positive relationships between those "treatments" and the innovative activity are necessary prerequisites for the success of the European Governments' Action Plan in order to secure long-term growth and employment. Our paper is the first empirical analysis that distinguishes subsidies for individual research and subsidies for collaborative R&D.

In the following section we describe the institutional background with respect to innovation policy in Germany and Finland. In Section 3 we summarize theoretical and empirical literature. Section 4 presents the hypotheses derived from economic theory, and outlines our econometric approach to assess the importance of public funding and collaboration on innovative activity. Furthermore, the data are described. Section 5 presents the estimation results, and Section 6 concludes.

2 Innovation policy in Germany and Finland

Finland and Germany belong to the European Union as well as to the OECD. Within this framework both countries are subject to a common currency area and commercial agreements, and a common European legal framework. As a distinctive feature, and in contrast to most European countries, Germany and Finland have (a) a comparable national innovation and R&D policy, (b) comparable policy instruments aimed at stimulating business R&D, and (c) a comparable public funding system.

Innovation policy rests on several pillars: direct subsidies for research projects within thematic programmes and promotion of SMEs in three promotion lines (innovation, co-operation, technology consulting), and by four types of support (grants, loans, venture capital and infrastructure supply). In general, firms can compose an individual mix of public support from of the different pillars that best suit the firm’s specific challenges. In contrast to other EU Member States, but in conformity with

Finland, no aspects of the fiscal treatment of innovation, such as tax credits or tax subsidies, are covered in Germany.[1] In both Germany and Finland direct subsidies are the most important innovation policy tools and two important policy trends have to be stressed: first, direct subsidies in R&D and innovation are given as "matched grants"[2] (cost sharing of total R&D project expenditures by the applicant and the government); second, as emphasized above, direct subsidies in R&D and innovation are preferably given to collaborative research projects.

Matching grants for R&D projects are directed to thematic programmes, adoptions of programme structures based on technology foresight, regular tenders and peer review-based selections, and special approaches (e.g. joint projects between industry and science or large firms and SMEs, regional networks, and start-ups). The administration of such business-related funding is delegated and carried out in Finland by Tekes (National Technology Agency) and in Germany by "project leaders" (Projektträger). Thus c*ollaborative research* for R&D projects is preferred because of their potentially beneficial effects such as positive spillovers, as well as cost and risk sharing.

Networking and close co-operations between universities and industry are seen as a key strength in Finland as well as in Germany. About 50% of the innovating companies in Finland have been involved in co-operative research and development. Judged by the frequency of use in 1998-2000, suppliers (41%), customers and clients (38%), and universities (29%) are the most important partners for collaborative research (Statistics Finland, 2002). According to OECD data, Finland has the second-largest share of firms with co-operation agreements with universities or government research institutes. Finland is also engaged in international co-operations. As a small country playing an active role in the programme definitions, Finland gains from contacts with the international research community. In Germany we find that, in total, 17% (1998-2000) of firms had any co-operation agreements; 15% of the German firms co-operated with partners in Germany and about 7% had foreign co-operation partners; 10% of German firms co-operated with universities.

The comparison between the German and the Finnish collaboration pattern reveals a strikingly higher propensity to collaborate in Finland. This observation does not only relate to the years 1998 to 2000 reported here; rather, we also find comparable results for the mid-1990s (see Foyn 2000). The reasons for this difference in the propensity to collaborate can be explained as follows: the small size of the Finnish economy facilitates networking by having comparably low transaction costs in finding the

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[1] Cf. the "Trend Chart on Innovation in Europe" for details on European policy schemes, or, in particular, for Germany, Rammer (2003), and Kutinlahti and Oksanen (2003) for Finland.

[2] In Germany direct project funding is carried out almost exclusively through grants; the Finnish funding system also grants loans to the companies. As the loans amount to less than 20% of the grants to firms and universities (Tekes 2004a), we do not explicitly distinguish grants and loans. Also, the data source used below will not allow a distinction between grants and loans.

right collaboration partner. But as we find rather large differences in the propensity to collaborate, even in equally sized economies such as Austria (cf. Foyn, 2000), size cannot be the whole story. More important than the size of the economy, we observe that strengthening of inter-firm networking and co-operation, as well as science-industry collaboration, has been a top priority of Finnish technology policy. One could argue that over the course of time a collaboration culture has been developed in Finland as it experiences a longer history with collaboration-targeted public funding policy than most of the other European countries (Schienstock and Hämäläinen, 2001). Since the National Technology Agency (Tekes) started its first technology programme in the early 1980s, collaboration has been a part of the financing principles (see e.g. Lemola, 2002). Tekes' notion of collaboration, however, is not focused on a special kind of collaboration; rather, it includes a whole plethora of different types of networks covering the whole spectrum of activities from basic R&D to marketing. It induces pre-competitive horizontal collaboration and vertical co-operation, as well as networks of small and medium sized companies with R&D institutions, or large companies, where the latter can hardly get funding unless they co-operate with SMEs or R&D institutes.

These differences in orientation towards collaboration in Germany and Finland make it an interesting question to analyze the outcome of collaboration including publicly stimulated collaboration in both countries. Such an analysis could shed some light on the success of public policy with respect to the European Action Plan.

3 Analysis of public funding, collaboration and patent outcome

3.1 Theory

The question of how and why firms engage in R&D collaborations and how that effects welfare emerged during the 1980s in economic literature (see Veugelers, 1998, for a survey). The industrial organization literature emphasizes the importance of knowledge spill-overs 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, and 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 benefit is higher than private return. This, of course, leads to underinvesment in innovative activity from a social point of view. R&D collaborations are one possibility to internalize such knowledge spill-overs and thus increase appropribility of returns within the research consortia. Three main issues are considered: coordination, free-riding and information sharing.

Coordination in such models is typically described through joint profit maximization. One finding is that investment in R&D when firms collaborate increases with the level of spill-over effects. A second result states that if spill-overs are high enough, that is, above some critical level, cooperating in R&D will result in higher investment compared to the status of no collaboration (cf. De Bondt and Veugelers, 1991). Cooperation always increases firms' profitability. Consequently, when spill-overs are high enough, firms have an increasing incentive to engage in R&D collaborations, and this should enhance welfare. It should be noted, however, that cost of coordinating R&D is often ignored in these models.

Collaborations bear the inherent risk of free-riding that may distorte the stability of cooperation. 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, 1994, Greenlee and Cassiman, 1999). Models find that cooperative agreements for being profitable and stable require that involuntarily outgoing spill-overs are not too high. This is in contrast with the results on coordination, where profits are higher with larger spill-overs. Here the profitability of collaboration increases with the firms' ability are to manage the outgoing spill-overs in order to protect against possible free-riding of partners.

Some models explicitly account for information sharing among partners, that is, managing spill-overs (e.g. Kamien et al., 1992, Katsoulacos and Ulph, 1998). Katsoulacos and Ulph model the choice of spill-overs and find the research joint ventures will always share at least as much information as non-cooperating firms, because research joint ventures maximize joint profits. Another issue for managing spill-overs 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 of others created through R&D activity. Kamien and Zang (1998, 2000) take that into account, and find ambiguous results with respect to R&D investment. Yet, collaboration is still the more profitable option.

In conclusion, theory states that non-collaborative R&D levels decrease with magnitude of spill-overs, while cooperative investments tend to increase with spill-overs, and thus imperfect appropriability of knowledge generating processes increase the benefits from collaborative agreements. If spill-overs are above a certain level, the "critical spill-over", co-operative R&D will result in higher investment than non-cooperative R&D. The presence of spill-overs increases the incentive for R&D collaboration through the internalization of the positive externality. Kamien and Zang show that result may no longer hold when absorptive capacity is taken into account, though. Information sharing increases the profitability of R&D cooperation. When spill-overs are high enough, collaborating firms will not only invest more in R&D, but are also more profitable than independently researching firms. Welfare is enhanced when spill-overs are large enough, but ambiguous when spill-overs are low. However, imperfect appropriability also encourages free-riding on R&D performed by other firm.

Theoretical results have initiated a whole debate on the implications of R&D collaborations for antitrust and the treatment of research joint ventures, leaving a favorable policy stance towards this type of cooperation (Ordover and Willig, 1985, Jacquemin, 1988, Shapiro and Willig, 1990). Although it seems to be an important policy conclusion leading to a 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 would facilitate product market collusion, the welfare enhancing results do no longer hold, of course. Hinloopen (2001) is one of the few papers that explicitly models the impacts of subsidies on collaborative and non-collaborative R&D.[3] The policy towards collaboration is not a subsidy, but only the legal opportunity to engage in R&D collaborations, though. Given this framework, he finds that the incentive to invest in R&D is higher for subsidies than the policy of allowing for collaboration. In a further step, Hinloopen shows that in case of optimally subsidizing cooperative or non-cooperative R&D leads to the same level of R&D activity. This suggests that "[...] sustaining R&D collaboratives is a redundant industrial policy, all else equal." (Hinloopen, 2001: 316)

Furthermore it should be stressed that the vast majority of theoretical models deals only with horizontal R&D co-operation, that is, with competitors. While this set-up is predominant in theory, it stands in stark contrast to survey evidence: most important partners are customers, suppliers and universities or other research institutions.[4] Empirically, collaboration with competitors is not found to be a significant case, at least in terms of frequency of collaborations. This is a large 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. Geroski (1992) states that since there is no presumption that the benefits of research joint ventures will be large or easily realized in every case, the design of the policy likely to be critical.

3.2 Empirical studies

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 was that most estimations in the reviewed studies 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 and this has to be taken into account. More recent studies correcting for selection include Busom (2000), Wallsten (2000), Lach (2002), Czarnitzki/Fier (2002) and

[3] See also Hinloopen (1997, 2000, 2001).

[4] It would be interesting to differentiate between horizontal and vertical collaboration. Unfortunately, our data does not allow to analyze horizontal collaborations in detail due to very low numbers of observations.

Almus/Czarnitzki (2003). 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 subsample 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 Israelian 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 Eastern German manufacturing where the government offers a high amount of subsidies in order to enhance the transformation process from a planned economy to a market economy sinve the German re-unification in 1990. They conclude that about 50% of R&D performed in Eastern Germany would not have been carried out in the absence of public innovation programs.[5]

Recent empirical studies have established that contractual forms of R&D, such as joint R&D, has become a very important mode of inter-firm and science-firm collaboration as the number of partnerships has largely increased (Sakakibara, 1997; Hagedoorn/Narula, 1996). Several papers that link theory and R&D collaborations are reviewed in Veugelers (2001). As one recent example, Cassiman and Veugelers (2002) explored the effects of knowledge flows on R&D co-operation. Their results suggest that firms with higher incoming spillovers and better appropriation have a higher probability of co-operating in R&D which confirms the arguments on spill-overs made by theoretical contributions.

Just a few empirical analyses deal with R&D co-operations as a part of firms’ innovative behaviour *and* as a policy instrument. Among those, Sakakibara (2001) analyzed Japanese government-sponsored R&D consortia over 13 years and found evidence that the diversity of a consortium is associated with greater R&D expenditure by participating firms. The results support the thesis that high spill-over effects occur. The magnitude of the effect of the participation in an R&D consortium on a firm’s R&D expenditures is found to be 9%, on average. Branstetter/Sakakibara (2002) examine the impact of government-sponsored research consortia on the research productivity in Japan by measuring their patenting activities over time. They find evidence that participants of research consortia tend to increase their patenting after entering a consortium, which is interpreted as evidence for spillovers above the "critical level". The marginal increase of participants’ patenting in targeted technologies, relative to the control firms, is large and statistically significant.

[5] Fewer studies deal with public policies and innovation outcome, such as employment or sales growth. See the survey by Klette et al., 2000, for examples of such studies).

4 Research design, econometric methodology and data

In line with the literature, we investigate how different firms' characteristics affect R&D and patenting activity. We distinguish four groups of innovating companies: (i) firms that neither participate in any collaborative innovation network nor receive public R&D funding (ii) firms that do not receive public R&D funding but are involved in R&D co-operations, (iii) firms which receive public funding but are not engaged in collaborative R&D, and (iv) firms which participate in collaborative research and receive public funding.

If spill-over effects in R&D co-operations are high, we expect that collaborating firms invest more in R&D and also patent more. Patents can be seen as a measure for successful R&D. In case, spill-overs are low, collaborating firms would invest less than non-collaborating firms. According to the theoretical results of Hinloopen (2001), there may be no difference between subsidized firms and collaborating firms. Furthermore, firms that receive subsidies and engage in collaboration would show the same activity as either collaborating firms or individually subsidized firms.

In the subsequent analysis we consider the receipt of public subsidies and the engagement in collaborations as heterogeneous "treatments" in order to disentangle effects due to collaboration and to public funding. Suppose there are M different states of treatments and the receipt of one particular treatment m is indicated by the variable $S \in \{0,1,\ldots,M\}$. The average treatment effects of the firms receiving m relative to l can be written as

$$E\left(\alpha^{m,l}\right) = E\left(Y^{m} \mid S = m\right) - E\left(Y^{l} \mid S = m\right) \tag{1}$$

where Y^{m} and Y^{l} denote the outcome in the different states. Given our possible combinations of public funding and collaboration, we can distinguish all cases of the treatment effect that are summarized in Table 1. Our different treatment states can take following different M "values": none, publicly funded, collaboration, and both publicly funded *and* collaboration.

Table 1: Research questions

		Actual state (m)			
		None	Collaboration	Public funding	Both
Counterfactual state (l)	None		1	2	3
	Collaboration	4		5	6
	Public funding	7	8		9
	Both	10	11	12	

Note: Reads from column to row: Case 1: "Given firms collaborate but are not subsidized, what would the innovative output be if they did not collaborate?"; Case 4: "For firms that neither collaborate nor are being subsidized, would collaboration increase the innovative output?".

Each case involves an estimate of a counterfactual situation, as for the companies in m we can only observe the actual value of the outcome but we cannot observe their output in the counterfactual situation *l*. However, the value of the outcome variable in the counterfactual situation is central to assessing the impact of the treatment. One cannot estimate $E(\alpha^{m,l})$ by just comparing two corresponding sub-samples of firms in state *m* and *l*. Neither the fact that companies receive public funding nor the fact that companies collaborate can be reasonably interpreted as the result of a random process. Both receiving funding as well as collaboration is subject to a possible selection bias. Concerning the funding, companies themselves choose to apply or not to apply for public funding, and the funding agency selects from the pool of applications based on certain criteria. As collaboration for innovation is part of the companies' innovation strategy, it is the companies themselves that choose whether or not to collaborate. The selection bias results in the empirical fact that the group of funded companies is different from the group of not funded ones, just as the group of collaborating companies is different from the group of not collaborating companies. Assessing the impact of a treatment based on a comparison of the group in state *m* with the group in *l* without correction for selection may generate misleading results.

The literature on the econometrics of evaluation offers different estimation strategies to correct for selection bias (see Heckman et al. 1999 for a survey), including the difference-in-difference estimator, control function approaches (selection models), IV estimation and non-parametric matching. The difference-in-difference method requires panel data with observations before and after/while the treatment (change of subsidy and collaboration status). As our database (to be described in the following subsection) consists of two pooled cross-sections where the majority of firms is only observed once, we cannot apply this estimator. For the application of IV estimators and selection models one needs valid instruments for the treatment variables. It is very difficult in our case to find possible candidates being used as instruments. Although the database contains a rich set of information on innovative activities, they cannot be interpreted as exogenous to the treatment. Again, the use of lagged values (before the treatment) is not possible due to the cross-sectional structure of the database. Hence the only appropriate choice is the matching estimator in our case. Its main advantage over the IV and selection models is that we neither have to assume any functional form for the outcome equation nor is a distributional assumption on the error terms of the selection equation and the outcome equation necessary. The disadvantage is that it only controls for observed heterogeneity among treated and untreated firms. However, as we discuss in the next subsection, we think that our set of covariates allows us to assume that selection on unobservable effects is unlikely.

Matching estimators have recently been applied and discussed by Angrist (1998), Dehejia and Wahba (1999), Heckman et al. (1998a, 1998b), and Lechner (1999, 2000). However, the usual case considered in the literature is just one binary treatment. Imbens (2000), Lechner (2001) and Gerfin and Lechner (2002) extend the matching to allow for multiple programmes. Matching is based on the insight that a counterfactual situation for companies in state *m* can be estimated from the sample of companies receiving *l*. The matching estimator amounts to creating a sample of firms in *l* that is comparable to the sample of firms in *m*, whereas comparability relates to a set of *a priori* defined characteristics (*X*). In the empirical application below we denote the estimated sample of state *l* as *matched controls*.

Conditioning on appropriate characteristics *X* results in the validity of the conditional independence assumption (Rubin, 1977) - that is, once the samples in states *m* and *l* have been balanced with respect to *X*, the outcome is statistically independent of the treatment. In this case one can compare the outcome of the group in state *m* with the selected control group from *l* having similar characteristics in *X*, and the observed outcome of the selected control group serves as an estimate for the counterfactual situation. Remaining differences in the outcome between both groups can thus be assigned to the treatment.

As the matching procedure requires the definition of the characteristics *X*, one might run into the curse of dimensionality problem. Suppose *X* contains only one variable. It would be intuitive to look for a control observation in state *l* that has exactly the same value in *X* as the corresponding firm in *m*. However, if the number of matching criteria is large, it would hardly be possible to find any control observation. Rosenbaum and Rubin (1983) have shown that it is sufficient to balance the samples on the propensity score. The idea is to use the propensity score for each treatment *M* for the whole sample and find pairs of firms from each sub-sample of interest that have the same probability of receiving treatments *M*. Balancing on the propensity score results in matched samples that are also similar in *X*. Suppose the choice probability of the alternative *j* conditional on *X* is $P(S=j|X=x)=P^{j}(x)$ and we want to calculate the effect of treatment *m* compared with *l* on the firms in *m*. Following Gerfin and Lechner (2002), the treatment effect can be calculated by

$$\begin{aligned} E\left(\alpha^{m,l} \mid S=m\right) &= E\left(Y^{m} \mid S=m\right) - E\left(Y^{l} \mid S=m\right) \\ &= E\left(Y^{m} \mid S=m\right) - \underset{P^{m}(X),P^{l}(X)}{E}\left\{E\left[Y^{l} \mid P^{m}(X), P^{l}(X), S=l\right] \mid S=m\right\} \end{aligned} \tag{2}$$

where the first term is just replaced by the mean value of the outcome variable of companies in state *m*, and the second term, the counterfactual situation, is replaced by the mean of the selected control group in *l*. Our matching protocol is summarized in Table 2 and follows Gerfin and Lechner (2002). As the propensity score is not known, it has to be estimated. We specify a seemingly unrelated probit model (also called bivariate dichotomous Probit model) incorporating each of our treatment cases (neither subsidized nor collaborating; only collaborating; only subsidized; and both), which allows for correlation among the equations' error terms.

We perform nearest neighbor matching. One difference of our application to the matching conducted by Gerfin and Lechner is that we do not pick just one control observation for each treated firm that is most similar in *X*, but pick two controls to improve the precision of the estimates.[6]

It is important to note that common support is required to achieve valid matching results - that is, all firms have the possibility of participating in all states. In practice, the samples are restricted to common support. For each treatment analysis, the observations with probabilities larger than the smallest maximum and smaller than the largest minimum of all sub-samples defined by *S* are deleted. In order to match on two propensity scores, we calculate the Mahalanobis distance to obtain a one-dimensional measure for the similarity of control observations.

Table 2: The matching protocol (nearest neighbor)

Step 1	Specify and estimate a probit model to obtain the propensity scores $\left[\hat{P}^0(X),\hat{P}^1(X),...,\hat{P}^M(X)\right]$.
Step 2	Restrict the sample to common support: delete all observations with probabilities larger than the smallest maximum and smaller than the largest minimum of all sub-samples defined by *S*.
Step 3	Estimate the counterfactual expectations of the outcome variables. For a given value of *m* and *l*, the following steps are performed: a) Choose one observations in the sub-sample defined by participation in *m* and delete it from that pool. b) Find an observation in the sub-sample of participants in *l* that is as close as possible to the one chosen in Step a) in terms of the propensity scores. Closeness is based on the Mahalanobis distance. Do not remove the selected controls from the pool of potential controls, so that it can be used again. Note that we require the selected control observations from *l* to belong to the same industry as the firms in *m*. c) Repeat a) and b) until no observation in *m* is left. d) Using the matched comparison group formed in c), compute the respective conditional expectation by the sample mean. Note that the same observation may appear more than once in that group.
Step 4	Repeat Step 3 for all combinations of *m* and *l*.
Step 5	Compute the estimate of the treatment effects using the results of Step 4.
Step 6	As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t-statitstic 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.

[6] Kernel matching would be an alternative that achieves higher efficiency than nearest neighbor matching, since it uses all observations from the control group to form an estimate of the counterfactual by weighting the control observation by similarity to the treated observation in question. However, this introduces a larger bias. We experimented with kernel matching, but that led to less successful matching results with respect to balancing the samples according to the covariates. Thus, we chose nearest neighbor as the bias is smaller; at the price of efficiency loss, though.

4.1 Data source, variables and descriptive statistics

The database is the Community Innovation Survey (CIS). The CIS, launched in 1991 jointly by Eurostat and the Innovation and SME Program, aims at improving the empirical basis of innovation theory and policy at the European level through surveys of innovation activities at enterprise level in the Member States. The CIS surveys collect firm-level data on innovation across Member States with largely harmonized questionnaires among countries. Thus the data are comparable on the European scale and are based on a representative sample of the economies. In this analysis we use the CIS II and CIS III spells referring to the years 1996 and 2000. Moreover, the data has been complemented by data taken from patent statistics. With regard to the German database, we only use Western German companies instead of all German companies since Western German firms are more comparable with Finnish companies, whereas Eastern German firms are still subject to the transformation from a planned economy to a market economy and may, therefore, not be appropriate candidates for a cross-country comparison between Finland and Germany. In particular, Eastern German firms have specific options for funding.

Both the German and the Finnish sample consist of firms that show at least some innovative activity (main focus of the CIS), and cover the manufacturing sector and important business services (IT services, R&D services and technical services). In Finland the CIS surveys firms with more than 10 employees, but in Germany it includes firms with more than five employees.

The main question of this analysis is whether the firms' innovation activities are stimulated by public funding and/or co-operations. R&D activity is measured as R&D intensity (*RDINT* = R&D expenditures / Sales); a standard variable in the literature. Patent activity is described by using a dummy variable *PATENT* indicating whether the particular firm has filed at least one patent application in the three years covered by the innovation survey.[7] In addition, we use patent counts per employee as dependent variable (*PATCOUNT*). The Finnish companies have a higher R&D intensity, on average: 6.5% versus 2.3% in the German case. For about 50% of German firm and 33% of Finnish firm observations, *PATENT* indicates at least one application.

As described above, treatments are indicated by two dummy variables: *CO* indicates firms that are engaged in collaborative research projects and *FUND* denotes publicly funded firms. The collaboration variable (*CO)* in this context means the active collaboration of all partners involved in the project. The mere contracting-out of R&D is definitely excluded from this definition. The share of firms performing collaborative research is about 34% in Germany but 62% in Finland. In the German

(Finnish) sample about 24% (48%) of all firms receive R&D subsidies. The share of firms receiving subsidies *and* engaging in collaboration (*FUND*CO*) is 14% in Germany and 39% in Finland. These large difference impressively reflect the Finnish policy efforts at fostering innovation.

We use other variables to control for firm heterogeneity, such as log of firm size measured as the number of employees (*LNEMP)*. The stock of patent applications per employee describes firms that show patent activity prior to the period under review (*PSTOCK*). In order to describe historical technological experience, we control for past applications in the long run; the patent stock is created from time series of patent applications at the firm level since 1985. In order to avoid endogeneity with our dependent variables, this variable is lagged three years - e.g. in CIS III the question on collaboration covers 1997 to 2000 and *PSTOCK* covers the years until 1996. The data is taken from the German and the Finnish Patent Office. In addition to previous patenting activities, the current potential to innovate does clearly depend on the firms' current R&D engagement. We measure this by a dummy variable indicating whether firms have an R&D department or not (*RDDEPT*). Six main sectors of economic activity are distinguished on the basis of the NACE classification. They capture the differences between the business sectors. Finally, a time dummy reflects changes in patenting activities over time (*YEAR*). See Table 3 for descriptive statistics of all variables used in the analysis.

Table 3: Descriptive statistics of the German and the Finnish sample

		Germany, N=1,043				Finland, N=1,459			
Definition	Variable	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
R&D intensity (in %)	*RDINT*	2.257	4192	0	52.19	6.491	12.178	0	70
Patent application (dummy)	*PATENT*	0.502	0.500	0	1	0.330	0.471	0	1
Patent appl. per employee	*PCOUNT*	0.017	0.045	0	0.556	0.009	0.040	0	0.954
Employees in 1,000s	*EMP*	0.500	2.117	0.006	62.941	0.352	1.416	0.01	24.25
R&D department (dummy)	*RDDEPT*	0.676	0.468	0	1	0.949	0.221	0	1
Patent stock per employee	*PSTOCK*	0.021	0.046	0	0.326	0.013	0.045	0	0.796
Export amount divided by turnover	*EXQU*	0.265	0.245	0	0.963	0.347	0.344	0	1
Group dummy	*GROUP*	0.451	0.498	0	1	0.515	0.500	0	1
Appropriability conditions	*APPR*	0.190	0.096	0	1	0.062	0.062	0	1
Public funding (dummy)	*FUND*	0.240	0.427	0	1	0.475	0.500	0	1
Co-operation (dummy)	*CO*	0.337	0.473	0	1	0.619	0.486	0	1
Publ. funding *times* cooperation	*BOTH*	0.139	0.346	0	1	0.376	0.485	0	1
Year 2000 (dummy)	*YEAR*	0.307	0.461	0	1	0.486	0.500	0	1

Note: The variables in the analysis also include 5 industry dummies not reported here.

[7] Most questions in the CIS survey cover three year-periods. Using CIS II and CIS III, therefore, covers 1994-1996 and 1998-2000.

The variables *PSTOCK*, *LNEMP* and *RDDEPT* are important characteristics to be considered in the selection equation, as governments pursue a picking-the-winner strategy. This means that in order to receive public funding firms should show previous successful innovation results (e.g. by patents) and prove that they maintain the capacity and capabilities to conduct the proposed research projects successfully. An obvious indicator for capacity is firm size, and that for capabilities is *RDDEPT*, of course. Those variables should not only be important to modelling the subsidy receipt but also the collaboration decision. On the one hand, firms can only benefit from spillovers if they maintain a critical mass of absorptive capacity; on the other hand, they must have something to offer (knowledge) to convince potential partners they would both benefit from co-operating. This is captured by *PSTOCK* and *RDDEPT*.

In addition, we control for firms that are associated with a group using a dummy variable *GROUP*. On one hand, firms that belong to a group may be more likely to collaborate. On the other, they may be less likely to receive public funding, as several public programs are restricted to small firms. Even if the firm is small, but capital is held by a large firm they do not qualify for programs only open for small (and medium-sized) firms. As emphasized by theoretical literature, appropriability conditions may play a role for the incentives for R&D collaborations, and such conditions vary over industries. We follow Cassiman and Veugelers (2002) and model appropriability at the NACE 3-digit industry level: in the CIS surveys, firms are asked on the sources of information for innovative activity. If they report that competitors are an important source of information, we create a dummy variable indicating this response. This dummy is averaged on industry 3-digit levels in order to measure appropriability conditions (*APPR*).[8] Using the important variables *LNEMP*, *PSTOCK* and *RDDEPT* along with industry dummies, and other controls are expected to describe the most important variables driving selection, and therefore we assume that the conditional independence assumption is fulfilled. We included polynomials and interaction terms of all variables with industry dummies and interactions among *LNEMP*, *PSTOCK* and *RDDEPT* in oder to test for possibly omitted variables, but such where jointly insignificant.

5 Estimation results

For the application of the matching estimator as outlined in Table 2, we first estimate a seemingly unrelated probit model on collaboration and public funding. From this estimation, we obtain the propensity scores (the predicted probabilties) that enter the matching routine as arguments.

[8] In addition to the variables described above, we also experimented with imports and concentration at the industry level, but neither of these variables exhibited a significant effect on the selection equations and we thus dropped them from our final specification.

The regressions yield comparable results for both countries. The differences relate to the influence of the export orientation on the companies' propensity to receive funding. In the Finnish sample we witness a significant positive influence. In the German sample the influence is not significant. As the National Technology Agency (Tekes), which distributes the largest fraction of the project-related funding in Finland, puts strong effort on the economic viability of the results of the funded project, special focus is put on the companies' competitiveness and the competitive advantage of the technology involved in the project (cf. Tekes 2004b). In a small open economy the companies' competitiveness in particular leads to an emphasis on export-oriented companies. In Germany, the association with a group reduces the probability of receiveing subsidies as it was expected, since small firms do not qualify for special SME programs if the capital is held by a large firm.

As expected, the correlation coefficient (*RHO*) is significant because collaboration and funding are linked to each other. This reveals the importance of collaborative research as a policy tool on R&D incentives.

Table 4: Seemingly unrelated probit models on public funding (FUND) and co-operation (CO)

	Germany			Finland		
FUND	Coef.		Std.err.	Coef.		Std.err.
LNEMP	0.159	***	0.038	0.198	***	0.028
RDDEPT	0.480	***	0.123	0.607	***	0.197
PSTOCK	2.157	**	0.931	5.681	***	1.090
EXQU	0.063		0.200	0.462	***	0.116
APPR	0.002		0.500	0.041		0.596
GROUP	-0.223	**	0.101	-0.093		0.083
Constant term	-0.855	***	0.188	-1.935	***	0.236
CO	Coef.		Std.err.	Coef.		Std.err.
LNEMP	0.183	***	0.037	0.221	***	0.030
RDDEPT	0.139		0.109	0.115		0.157
PSTOCK	2.262	**	0.907	4.701	***	1.125
EXQU	0.404	**	0.189	0.249	**	0.118
APPR	-0.001		0.466	0.368		0.669
GROUP	0.105		0.093	0.227	***	0.082
Constant term	-0.798	***	0.178	-0.788	***	0.201
RHO	0.403	***	0.052	0.474	***	0. 039

Note: *** (**, *) indicates a significance level of 1% (5%, 10%). All estimations include 5 industry dummies and one time dummy.

A necessary condition for the consistency of the matching estimator is common support, but, as stated above, the samples are often restricted to common support in practice. If there would be no overlap of propensity scores among groups, or it would be too small, the matching estimator is not applicable. Table 5 presents the impact of the common support restriction for each group considered in the following matching analysis. The lost observations amount to about 6.2% in the German sample and 7.4% in the Finnish one. Those firms are typically very small and do not have an R&D department. We therefore assume that the results are not considerably affected by the common support requirement. Note that the share of observations without common support is typical in the case of heterogenous treatments, because by construction the control group is smaller than the treatment group in several comparisons of states *l* and *m* (cf. Gerfin and Lechner, 2002).

Table 5: Initial sample per group and loss due to common support restriction

	Germany		Finland	
	Initial sample	Lost due to common support restriction	Initial sample	Lost due to common support restriction
Firms that neither collaborate nor receive subsidies	586	7.8%	412	7.3%
Collaborating firms	207	2.4%	354	5.9%
Publicly funded firms	105	3.8%	144	2.8%
Firms that receive subsidies and also collaborate	145	6.9%	549	9.7%
	1,043	6.2%	1459	7.4%

As we imposed one additional restriction, namely that the selected controls belong to the same industry as the respective treated firms, a further check on the successful balancing of the covariates was performed after the matching. We used an indicator variable describing the states *m* and *l*, and regressed that on all covariates with the matched samples for each case. The requirement for a successful matching is the Wald test on the hypothesis that all coefficients are jointly zero in this regression. This is fulfilled for all the results presented below. Also individual t-test on mean differences in covariates among groups confirmed that the samples are well balanced after matching.

For the matching, we pick the two nearest neighbors for each firm to be evaluated. Table 6 presents the matching results in the German sample. The main diagonal shows the unadjusted shares of the dependent variable of the groups reported in the columns. With regard to the actually treated compared with the non-treated (Cases 1, 2 and 3), Cases 1 and 3 exhibit a significant positive effect for the case of R&D intensity. We do not find a significant effect in Case 2, which considers publicly funded firms compared with non-treated ones. These results suggest with respect to the spill-over debate in theoretical literate that, first, spill-overs are indeed above a certain threshold level so that collaborating firms increase R&D. Second, the positive spill-over effect outweighs potentital disadvantages through free-riding, for instance. With respect to potential that could be stimulated, we find that firms that do neither collaborate nor receive subsidies would benefit significantly from engaging in reserach networks (Case 10). The same does even apply for collaborating firms (Case 11) and for publicly funded firms (Case 12). Both groups of firms would benefit from membership in publicly subsidized research networks, and increase R&D spending even more.

For the patent dummy, we find similar effects: firms that actually collaborate and those that collaborate and receive funding would perform worse if they either would not collaborate or would not collaborate and not receive subsidies. Firms currently not engaged in collaborations (subsidized or not) would significantly benefit (Cases 4 and 10). The evidence on patent counts per employee, however, is disappointing. Not a single treatment effect turns out to be significant. We attribute this effects at least partly to the fact of small sample sizes in groups in combination with a highly skewed distribution on patent counts.

Table 6: Matching Results for Germany: Average Treatment Effects $E(\alpha^{m,l})$

		Actual state (*m*)			
		Dependent variable: R&D Intensity (R&D expenditures/Sales)			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None	1.591	1) 0.775** (0.035)	2) 0.278 (0.424)	3) 2.533*** (0.056)
	Collaboration	4) -0.096 (0.325)	2.224	5) 0.103 (0.596)	6) 2.195*** (0.607)
	Public funding	7) -0.276 (0.506)	8) 0.335 (0.480)	2.497	9) 1.903*** (0.654)
	Both	10) -2.420*** (0.842)	11) -2.143*** (0.792)	12) -1.608** (0.820)	4.821
		Dependent variable: patent dummy			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None	0.367	1) 0.101** (0.051)	2) 0.094 (0.067)	3) 0.111** (0.056)
	Collaboration	4) -0.158*** (0.053)	0.657	5) -0.045 (0.075)	6) 0.026 (0.060)
	Public funding	7) -0.047 (0.069)	8) -0.023 (0.071)	0.571	9) -0.019 (0.065)
	Both	10) -0.198*** (0.068)	11) -0.040 (0.060)	12) -0.104 (0.077)	0.779
		Dependent variable: number of patents per employee			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None	0.011	1) 0.001 (0.005)	2) 0.006 (0.006)	3) 0.006 (0.006)
	Collaboration	4) -0.004 (0.004)	0.020	5) 0.002 (0.007)	6) 0.003 (0.007)
	Public funding	7) 0.001 (0.004)	8) -0.003 (0.007)	0.021	9) -0.0003 (0.008)
	Both	10) -0.006 (0.005)	11) -0.0002 (0.005)	12) -0.006 (0.009)	0.033

Standard errors in parentheses. *** (**,*) indicates a 1% (5%, 10%) significance level (two-sided test). Standard errors are obtained with Lechners (1999) asymptotic approximation correcting for replicated observations due to sampling with replacement. The main diagonal shows the unadjusted averages of the dependent variables of the groups in columns.

We conclude that collaboration (and the combination of collaboration and subsidies) leads to improved innovative performance in the economy, at least in the case of R&D spending and general patent activity as described by the dummy, and there is still potential that could be exploited by setting incentives for collaboration. In line with the finding that funding alone has no significant effect, we find that increased public funding of individual research does not seem to be promising strategy to foster innovation output.

Table 7: Matching Results for Finland: Average Treatment Effects E($\alpha^{m,l}$)

		Dependent variable: R&D Intensity (R&D expenditures/Sales)			
		Actual state (*m*)			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None	3.269	1) 1.664*** (0.6435)	2) 5.800*** (1.447)	3) 6.537*** (0.786)
	Collaboration	4) -1.596** (0.762)	4.527	5) 3.955** (1.546)	6) 4.091*** (0.966)
	Public funding	7) -3.745** (1.775)	8) -1.585 (1.635)	8.876	9) 1.658 (1.960)
	Both	10) -9.010*** (1.478)	11) -4.102*** (0.990)	12) -3.414* (1.784)	8.826
		Dependent variable: patent dummy			
		Actual state (*m*)			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None	0.123	1) 0.106*** (0.036)	2) 0.137*** (0.050)	3) 0.281*** (0.043)
	Collaboration	4) -0.072** (0.035)	0.267	5) 0.035 (0.057)	6) 0.143*** (0.044)
	Public funding	7) -0.119* 0.065	8) -0.023 (0.067)	0.271	9) 0.178*** (0.062)
	Both	10) -0.175*** (0.041)	11) -0.100** (0.042)	12) -0.132** (0.058)	0.516
		Dependent variable: number of patents per employee			
		Actual state (*m*)			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None	0.003	1) 0.002 (0.002)	2) 0.004* (0.002)	3) 0.012*** (0.003)
	Collaboration	4) 0.001 (0.002)	0.005	5) -0.002 (0.003)	6) 0.010*** (0.003)
	Public funding	7) -0.0001 (0.003)	8) 0.001 (0.003)	0.006	9) 0.009** (0.004)
	Both	10) 0.006* (0.003)	11) -0.005 (0.004)	12) -0.019*** (0.07)	0.010

Standard errors in parentheses. *** (**,*) indicates a 1% (5%, 10%) significance level (two-sided test). Standard errors are obtained with Lechners (1999) asymptotic approximation correcting for replicated observations due to sampling with replacement. The main diagonal shows the unadjusted averages of the dependent variables of the groups in columns.

The Finnish data reveals the following effects for the case of R&D intensity (see Table 7): first, collaboration and funding (and both) result in increased R&D spending compared with no treatment (Cases 1, 2 and 3). Again, this points to the conclusion with respect to cooperative research that spill-over effects in collaborations are supposedly high enough that firms increase R&D compared to non-cooperative research. In contrast to Germany, Finnish firms spend significantly more on R&D when they receive subsidies (Case 2). There is also potential for public policy left: for firms that are currently neither engaged in collaboration nor receive public funding we find that they would benefit significantly from either subsidies, collaboration or both (Cases 4, 7 and 10). Also firms that do either collaborate or receive subsidies, would increase R&D if they were engaged in both (Cases 11 and 12).

The finding concerning the patent dummy point basically into the same direction. The same pattern that is found for R&D intensity results for the patent dummy. Thus, high spill-over effects in cooperative research does not only lead to increased R&D spending, but also translates into more patent activity. In the case of patent counts per employee, we observe the same phenomenon as in the German sample. Although the treatment effects point in the same direction as in the regressions using the patent dummy, the significance levels of estimated effects go down. However, we still find a stron effect in Cases 3, 6 and 9, which implies that firms actually engaged in collaboration and public policy programs would perform worse if they would abandon one of the strategies. Furthermore, there is a strong effect predicting a performance increase for firms that actually receive funding if they would also enter cooperative research. Again spill-over effects would potentially enhance performance.

6 Conclusion

This study focused on the impact of innovation policies and R&D collaboration in Germany and Finland. In the context of the "Action Plan 2010" by the European Council, we investigated whether public R&D subsidies have a positive impact on the innovation output. This mechanism is a necessary condition for the success of the European efforts to catch up with the US and Japan and close the emerging technology gaps. As special emphasis has been laid on public incentives for collaborative research in recent years, we took particular account of joint R&D. In this paper we analyzed the effects of public incentives and R&D collaboration on R&D expenditures and the innovative output of companies measured by their patenting activity.

Economic theory has no clear prediction on the effects of cooperative research on R&D expenditure. If spill-over effects are low, firms would reduce R&D. In constrast, sufficiently high spill-over effects would lead to increased R&D expenditure. However, the risk of free-riding on partners' R&D activities may counterveil the positive effects due to spill-overs.

We conducted a treatment effects analysis to assess whether funding and/or collaboration yields a positive benefit in terms of R&D and patent activity. We interpreted collaboration and subsidies as heterogeneous treatments and considered an econometric matching, taking a possible selection bias into account. Our results show that in Finland R&D collaboration and R&D subsidies yield positive treatment effects in the groups actually receiving such treatment, compared with the situation in the absence of treatments. In Germany we cannot support this hypothesis for firms that receive R&D

subsidies for individual research. In addition, we find innovation potential in the group of non-treated firms that could be utilized by collaboration (including the combination with subsidies), but is currently not exploited. Furthermore, the results show in both countries that firms that actually receive subsidies or collaborate would increase R&D spending if they would combine subsidies and cooperative research. Thus we conclude that in cooperative research, spill-over effects seem to be high enough to generate the incentive to invest more in R&D. This effect also outweighs potential negative effects on R&D engagement through free riding.

In Finland, the results do not only apply for R&D subsidies, but also for patenting activity. For instance, if firms invest more in R&D induced by collaboration or subsidies (or both) this effect also translates into innovation output as measured by patent activity. In Germany, we find similar patterns but results concerning innovation output are less pronounced.

Hence the main conclusion of our analysis is that public incentives and collaboration have a positive impact on the treated firms in Finland. In Germany, however, only collaboration and the combination of subsidies with collaboration show significant effects. We find support for this crucial mechanism and policy makers can improve Europe's innovative performance by means of the "Action Plan 2010" - incentives for R&D collaboration seem a particularly promising recipe.

However, it should be stressed that the positive effects induced by spill-overs in cooperative research will only increase welfare if they do not lead to collusion in product market. This is a serious issue and should be subject for further research. In addition, having panel data to advance with a difference-in-difference estimator would be desirable, because it rules out fixed effects possibly affecting the results to some extent. In particular, the conditional difference-in-differences approach (DiD on matched samples) would be an interesting extension of our work.

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