Discussion Paper No. 04-37

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

Dirk Czarnitzki, Bernd Ebersberger and Andreas Fier

ZEW
Zentrum für Europäische Wirtschaftsforschung GmbH
Centre for European Economic Research

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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*

May 2004

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 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 on patent activity, 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 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

*	Dirk Czarnitzki, Andreas Fier	**	Bernd Ebersberger
Address:	Centre for European Economic Research (ZEW)		Technical Research Center of Finland (VTT)
	Department of Industrial Economics and International Management		Group for Technology Studies
	P.O. Box 10 34 43		P.O. Box 1002
	D-68034 Mannheim		FIN-02044 VTT
	Germany		Finland
Phone:	+49/621/1235-158, -180		+358/9/456-4238
Fax:	+49/621/1235-170		+358/9/456-7007
E-mail:	czarnitzki@zew.de, fier@zew.de		bernd.ebersberger@vtt.fi

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 Bernd Fitzenberger, Heinz Hollenstein, Guido W. Imbens, Jordi Jaumandreu, Michael Lechner, Jacques Mairesse and Pierre Mohnen for helpful comments.

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 competitive reasons, 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 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.

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 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. 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. In the following section we describe why it is particularly interesting to compare Germany and Finland as Member States on this topic. In Section 3 we outline our empirical approach to assessing the importance of public funding and collaboration on innovative outcome, the econometric methodology and describe the data. Section 4 presents the estimation results, and Section 5 adds some additional empirical evidence from a difference-in-difference estimation in the German sample. Section 6 concludes.

2 General trends of innovation policy in Germany and Finland

The trends of the government’s expenditure on R&D and innovation are important indicators of where scientific progress is to be advanced with government funding. The comparison of Finnish and German innovation policy trends is of particular interest because both countries have similar policies but achieved different success in recent years.

2.1 Policy

Finland and Germany *inter alia* 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. Both countries contribute common economic indicators to the OECD for cross-country comparisons, and innovation is a priority of all Member States of the European Union. Throughout Europe, hundreds of policy measures and support schemes aimed at fostering innovation have been implemented or are under preparation. The diversity of these measures and schemes reflects the diversity of the framework conditions, cultural preferences and political priorities in the Member States. 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. Cassiman/Veugelers (2002) and Dachs/Ebersberger/Pyka (2004) in an empirical study explore 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.

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

[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.

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 right collaboration partner. But as we find rather large differences in the propensity to collaborate, even in equally sized economies such as Austria (cf. Dachs/Ebersberger/Pyka, 2004; 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.

2.2 Macroeconomic innovation indicators

In various international comparisons Finland ranks as one of the leading European countries for innovation, as measured in terms of growth, competitiveness, technological sophistication and infrastructure. The EU's science and technology indicators show Finland, Sweden and Denmark to be countries that are rapidly transforming into knowledge-based economies. In general, the Finnish catching-up process was heavily determined by its fundamental structural shift from a resource-based economy to a knowledge-based economy; R&D was a key factor in this development. The Finnish R&D growth over the course of the 1990s outpaced that of all other OECD countries except Iceland, and at the end of the 1990s Finland was by far the biggest R&D spender (relative to GDP) of all OECD countries (cf. Werner, 2003). At the same time, Germany had to cope with the consequences of reunification in 1989. The former East Germany had to find its way from a planned economy to a market economy. During this time the budgets in all areas of German life were severely strained by the massive efforts of the reunification process.

Table 1 summarizes the development of the gross domestic expenditure on R&D (GERD) during the 1990s in both countries. While the GERD to GPD ratio was higher in Germany in 1991, Finland realized higher growth rates during the 1990s and achieved a ratio that is almost 1 percentage point higher than in Germany in 2001. During the same period, the private share of GERD increased from about 56% to 71% in Finland, whereas it only grew from 62% to 66% in Germany. It should, however, be noted that aggregate R&D expenditure in Finland is to a large degree shaped by the private ICT sector (Nokia effect). The importance of the electronics industry rose from the early 1990s to the late 1990s, increasing its share of private R&D expenditure from about 25% in 1990 to about 54% in 1999 (Statistics Finland, 2001). Thus Nokia became the “third leg of Finland’s economy” besides Wood and Paper, and Metal (see Mosaic Group, 1998, Ali-Yrkkö et al., 2000).

Table 1: Relative Gross Domestic Expenditure on R&D: Germany and Finland

	Germany					Finland				
	Share of GERD		Share of GDP			Share of GERD		Share of GDP		
	Private	Public	Private	Public	Total	Private	Public	Private	Public	Total
Year	%	%	%	%	%	%	%	%	%	%
1991	61.86	35.68	1.57	0.90	2.53	56.32	40.90	1.14	0.83	2.03
1993	61.91	36.12	1.46	0.85	2.35	56.62	39.83	1.22	0.86	2.16
1995	61.13	36.80	1.38	0.83	2.26	59.47	35.09	1.36	0.80	2.28
1997	61.36	35.90	1.41	0.82	2.29	62.90	30.86	1.71	0.84	2.71
1999	64.96	32.55	1.58	0.79	2.44	66.95	29.18	2.16	0.94	3.23
2001	65.99	31.53	1.64	0.78	2.49	70.78	25.52	2.41	0.87	3.40

Source: OECD, 2003.

Along with the scientific value and the knowledge acquired, the primary objective of both German and Finnish research is to make the most effective and efficient commercial use of R&D results. In international statistics the innovative capacity is often measured by patents (cf. Griliches, 1990, or OECD, 1994, for discussions on the use of patents as science and technology indicators). Macroeconomic figures show that besides “input” indicators like GERD, innovation outcome indicators, such as patents, have scored a remarkable catching-up process in Finland in the 1990s. The number of patents as an output variable is seen as an important yardstick of the technological competitiveness in the future. Table 2 demonstrates the impressive growth of Finnish patenting activities. Finland's growth in patenting activities at the European Patent Office (EPO) largely outperforms Germany and is much above the average in the European Union. The number of triadic patent families shows a similar trend.[3]

If the recent innovation performance of countries is partly due to government incentives for R&D, the European Council's Action Plan 2010 aiming at securing long-term growth and employment may be successful. As a positive hint at such mechanisms, one should find a link between public policies and firms' innovative output. A comparison between Germany and Finland seems to be a reasonable choice, because Germany is the largest economy in the EU and has only shown 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. If there are positive policy effects in both countries, we can conclude that the Action Plan 2010 is promising with regard to growth and employment in the European Union.

Table 2: Numbers of patent applications in Finland and Germany

	Development of the number of patent applications to the EPO (priority year), 1990=100			Development of the number of triadic patent families (priority year), 1990=100		
	Germany	Finland	European Union	Germany	Finland	European Union
1991	98,9	96,7	99,7	89,5	107,7	91,7
1993	102,6	135,4	103,2	96,9	164,3	98,3
1995	113,7	162,5	114,5	116,8	207,1	115,2
1997	152,2	233,4	149,2	133,2	263,3	131,6
1999	182,2	322,0	177,6	140,0	263,3	134,9

Source: OECD, 2003.

The following section outlines our research design on the question of whether those increases in innovative output are (partly) due to public incentives for R&D. As a main focus we take the most important policy, the funding of collaborative research, into account.

3 Analysis of public funding, collaboration and patent outcome

3.1 Literature

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

[3] "A patent is a member of the [triadic] patent families if, and only if, it is filed at the European Patent Office (EPO) and the Japanese Patent Office, and is granted by the US Patent and Trademark Office (USPTO)" (OECD, 2003).

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 Almus/Czarnitzki (2003). Fewer studies deal with public policies and aspects differing from crowding-out effects, like co-operation and innovative output (see the survey by Klette et al., 2000, for examples of such studies).

The question of how and why firms engage in collaborations, partnerships, alliances, joint ventures and networks emerged during the 1980s in economic literature. Different theories and empirical studies have analyzed the mechanisms within research consortia and their benefits and a detailed discussion is far beyond the scope of this paper. Important contributions have been provided by Katz (1986), d'Aspremont/Jacquemin (1988), Freeman (1991), Kamien et al. (1992), Katsoulacos/Ulph (1998), Robertson/Gatignon (1998), Kamien/Zang (2000), and Cassiman/Veugelers (2002). Link et al. (2002) and Hagedoorn et al. (2000) give overviews of strategic research partnerships, taking public financial support to firms into account. 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). Just a few articles and empirical investigations 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 spillover 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. The marginal increase of participants' patenting in targeted technologies, relative to the control firms, is large and statistically significant.

3.2 Research design and econometric methodology

In line with the literature, we investigate how different firms' characteristics affect the probability to patent. 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 significant benefits are produced by collaborative research activities, we hypothesize that firms participating in R&D networks will exhibit a higher innovation productivity resulting in increased patenting activities due to positive knowledge spillover effects. Hagedoorn and Cloodt (2003) analyze how different indicators describe the innovativeness of firms and point out that patents "could be a more than acceptable indicator of innovative output" (Hagedoorn and Cloodt 2003, p.1366). Hence our results can be interpreted in terms of innovative output in general. In the following discussion we use patenting and innovative output synonymously.

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 $S \in \{0,1,...,M\}$. The average treatment effects of the firms receiving m relative to l can be written as

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

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 3. Our different treatment states can take following different M "values": none, publicly funded, collaboration, and both publicly funded *and* collaboration.

Table 3: 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	

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 (patent activity) 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

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

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 4 and follows Gerfin and Lechner (2002). As the propensity score is not known, it has to be estimated. We specify a multinomial probit model incorporating each of our treatment cases (collaboration, R&D funding and both). Those propensity scores express the propensity to enter each treatment status relative to our reference category, the firms that neither collaborate nor receive funding. The model is estimated by simulated maximum likelihood using the GHK simulator in order to take account of these correlations. Note that a "standard" multinomial logit does not account for correlations and requires the independence of irrelevant alternative assumptions, which is usually violated in empirical applications (see Train, 2002, for a textbook discussion on the multinomial probit model). 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.

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 4: The matching protocol

Step 1	Specify and estimate a multinomial 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.

3.3 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 samples consist of firms that show at least some innovative activity (main focus of the CIS), which means that these firms either introduced one or more new products (or significantly improved products) or one or more new processes (or significantly improved processes). We 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. Moreover, the firms in Finland are much smaller than in Germany, on average. In order to have more comparable samples, we have excluded the largest firms from the analysis and dropped the firms that are smaller than ten employees from the German data. Hence both samples cover firms from ten employees up to firms with 2,500 employees.

The main question of this analysis is whether the firms' patenting activities are stimulated by public funding and/or co-operations. This patent activity is measured in the empirical analysis 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.[4] We do not use the number of patent applications because the distribution of this variable is very skewed in the economy and all results would possibly be biased towards the patenting activities of a few huge companies. Even rescaling the number of applications by the number of employees does not significantly reduce the skew. Therefore, we use a dummy variable that shows if policy and collaboration have broad effects on the economy and not only on one or two exceptional patentees. For about 44% of German firm and 26% of Finnish firm observations, *PATENT* indicates at least one application. While the growth of innovation in Finland outperforms most European countries (see Section 2), we observe that the average innovative activity is substantially larger in Germany.

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 29% in Germany but 64% in Finland. In the German (Finnish) sample about 21% (48%) of all firms receive R&D subsidies. The share of firms receiving subsidies *and* engaging in collaboration (*FUND*CO*) is 11% in Germany and 39% in Finland. This huge difference impressively reflects 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).* Note that even the limitation to firms with 2,500 employees at most

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

does not lead to comparable firm sizes in both countries. While the average number of employees is 312 in Germany, it is only 182 in Finland. A dummy indicates firms that show patent applications prior to the period under review (*LAGPAT*). To describe historical technological experience, we control for past applications in the long run; the dummy takes the value equal to one if the corresponding firm shows at least one patent application since 1985 and is zero otherwise. In order to avoid endogeneity with our dependent variable, this variable is lagged three years - e.g. in CIS III the question on collaboration covers 1997 to 2000 and *LAGPAT* covers the years until 1996. The data is taken from the German and the Finnish Patent Office.[5] The descriptive statistics show that there seems to be a strong dependence over time, because the share of firms with previous patent applications is as high as the share of patenting firms in the period under review. This emphasizes the great importance of *LAGPAT* as a control variable in the matching process. In addition to previous patenting activities, the current potential to patent does clearly depend on the firms' current R&D engagement. We measure this as the number of R&D employees divided by *EMP* to reduce collinearity with firm size (share of R&D employees: *RDEMP)*. Once again we find that the R&D activities measured by *RDEMP* is higher in Germany than in Finland, on average. Six main sectors of economic activity are distinguished (*INDUSTRY*) 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 5 for descriptive statistics of all variables used in the analysis.

Table 5: Descriptive statistics of the German and the Finnish sample

		Germany, N=1,464				Finland, N=1,520			
Definition	Variable	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
Patent application (dummy)	*PATENT*	0.438	0.496	0	1	0.259	0.437	0	1
Employees in 1,000s	*EMP*	0.312	0.401	0.011	2.5	0.182	0.214	0.01	2.025
Share of R&D employees	*RDEMP*	0.087	0.187	0	1	0.076	0.117	0	1
Patent stock (dummy)	*LAGPAT*	0.439	0.496	0	1	0.275	0.433	0	1
Export amount divided by turnover	*EXQU*	0.242	0.239	0	1	0.342	0.314	0	1
Public funding (dummy)	*FUND*	0.208	0.406	0	1	0.483	0.500	0	1
Co-operation (dummy)	*CO*	0.287	0.452	0	1	0.643	0.479	0	1
Public fund. *times* Co-op. (dummy)	*BOTH*	0.110	0.313	0	1	0.386	0.487	0	1
Year 2000 (dummy)	*YEAR*	0.333	0.401	0	1	0.602	0.490	0	1

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

The variables *LAGPAT*, *LNEMP* and *RDEMP* are important characteristics to be considered in the selection equation, as governments pursue a picking-the-winner strategy. This means that in order to

[5] Again we consider a dummy variable instead of the patent stock, unlike Czarnitzki/Fier (2003) for example,

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 *RDEMP*, 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. Both factures are captured by *LAGPAT* and *RDEMP*. Admittedly, *RDEMP* holds some possible danger of causing endogeneity, at least in the policy equation if firms hired additional personnel due to a recent subsidization. Unfortunately, we cannot rule this problem out by using lagged values for *RDEMP*, as this information is not available in the database and the discussion above shows that it is very important to include *RDEMP* as a covariate. Note, however, that if some endogeneity does occur, we would underestimate the actual treatment effect on the treated due to this flaw in the model. If we find positive effects, this problem is negligible. In addition to the variables described above, we also experimented with imports and concentration on the industry level as well as appropriability conditions as modelled by Cassiman and Veugelers (2002), but neither of these variables exhibited a significant effect on the selection equations and we thus dropped them from our final specification. Using the important variables *LNEMP*, *LAGPAT* and *RDEMP* along with industry dummies, the time dummy and exports are expected to describe the most important variables driving selection, and therefore we assume that the conditional independence assumption is fulfilled, especially as we include several interaction terms of the variables used in the estimation of the propensity scores (see below).

4 Estimation results

4.1 Probability to patent

As a first step, we consider *CO* and *FUND* as exogenous and regress the patent dummy (*PATENT*) on our explanatory variables, including an interaction term *CO*FUND*. As shown in Table 6, we first find that firms that have been funded (*FUND*) exhibit a significantly higher probability to file a patent than non-funded firms in both Germany and Finland. We also find a positive impact of the collaboration dummy (*CO*) on the propensity to patent in both countries. *CO*FUND* is insignificant. The patenting history (*LAGPAT*) has a strong positive influence on the propensity to patent. Further results in Table 6 reveal the expected effects of the control variables; larger firms are more likely to

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due to the skew of the patent stock based on the number of applications.

file a patent and the share of R&D employees representing the current resources spent on innovative activities shows a strong effect on the probability to patent.

We also computed marginal effects on the probability to patent, including their standard errors obtained by the delta method (calculated at the sample means). In Germany (Finland) collaboration increases the probability to patent by 16 percentage (13) points and funding has an effect of 20 percentage (10) points. These marginal effects are significant at the 1% level.

Table 6: Probit estimations on patenting activity (PATENT)

	Germany		Finland	
PATENT	Coef.	Std.err.	Coef.	Std.err.
LNEMP	0.280 ***	0.035	0.214 ***	0.033
RDEMP	0.762 ***	0.226	1.061 ***	0.297
LAGPAT	0.936 ***	0.086	0.892 ***	0.085
EXQU	0.937 ***	0.181	0.406 ***	0.133
FUND	0.395 ***	0.135	0.365 ***	0.161
CO	0.518 ***	0.104	0.486 ***	0.128
*FUND*CO*	-0.336	0.205	-0.025	0.188
Constant term	-0.847 ***	0.127	-1.574 ***	0.164
Log likelihood	-655.322		-651.199	
McFadden R^2	0.347		0.282	

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

4.2 Matching

We now address the problem of a selection bias and consider *CO* and *FUND* as endogenous variables. As described in Section 2, we expect a high correlation between collaborative research and public funding as research networks are today's most important policy tool in Germany and Finland. To illustrate this we use our remaining variables as covariates, *X*, representing important characteristics on which the treated and corresponding control samples should be balanced afterwards, and estimate the multinomial probit model using the GHK simulator, allowing for correlation among alternatives. The results are given in Table 7.

Fundamentally, we obtain support for the assumed selection bias as the group of funded (collaborating) companies is significantly different from the group of non-funded (non-collaborating) companies. 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.

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 7: Multinomial probit model using the GHK simulator on public funding (FUND) and co-operation (CO)

	Germany			Finland		
FUND	Coef.		Std.err.	Coef.		Std.err.
LNEMP	0.112	***	0.034	0.167	***	0.028
RDEMP	1.087	***	0.199	2.198	***	0.285
LAGPAT	0.325	***	0.092	0.394	***	0.083
EXQU	0.130		0.175	0.507	***	0.119
_CONS	-0.954	***	0.125	-0.423	***	0.115
CO	Coef.		Std.err.	Coef.		Std.err.
LNEMP	0.169	***	0.032	0.276	***	0.028
RDEMP	0.940	***	0.193	1.851	**	0.308
LAGPAT	0.262	***	0.085	0.268	***	0.088
EXQU	0.459	***	0.165	0.292	**	0.124
_CONS	-0.888	***	0.122	0.852		0.122
RHO	0.382	***	0.046	0.423	***	0. 040

Note: *** (**, *) indicates a significance level of 1% (5%, 10%). All estimations include 5 industry dummies and one time dummy; the SML estimations were performed using 200 draws in the simulator. Firms that receive no treatment are the reference group.

Note that we do not use the estimation presented above to generate the propensity scores for the upcoming matching process. In order to allow for a more flexible functional form, and to achieve a better approximation of the conditional independence assumption, we create several interaction terms of the variables and re-estimate the model presented in Table 7, including following additional regressors: the interaction terms of *LNEMP*, *RDEMP* and *PATSTOCK*, and the three variables multiplied by the time and industry dummies, amounting to 42 additional regressors (21 in each equation of the model. An LR test shows that these additional regressors have additional explanatory power in the model ($\chi^2(42) = 74.87$ in Germany and 72.51 in Finland).

A necessary condition for the consistency of the matching estimator is common support. Once the propensity scores are estimated, we drop the firms lacking common support. Table 8 presents the impact of the common support restriction for each group considered in the following matching analysis. The lost observations amount to about 16% in the German sample and only 6% in the Finnish one. The vast majority of dropped observations in Germany belong to the group that neither receives funding nor is subsidized. Those firms are typically very small and do not show any patenting activity or a significant share of R&D employees. We therefore assume that the results are not considerably affected by the common support requirement.

Table 8: 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	901	21.5%	394	4.8%
Collaborating firms	259	7.7%	392	2.6%
Publicly funded firms	143	7.7%	148	3.4%
Firms that receive subsidies and also collaborate	161	7.5%	586	10.4%
	1,464	16.2%	1,520	6.3%

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.

Note that we chose two neighbours for each firm to be evaluated, except in Cases 4, 7 and 10 in Germany. Cases 4, 7 and 10 amount to the average effects on untreated firms. As those groups are larger than the remaining groups in Germany it was impossible to find two close neighbours, and we just drew one control observation in those cases. In a few cases we also included *RDEMP* as an additional matching criterion in the calculation of the Mahalanobis distance. For the computation of case 8, 9 and 12 in the Finnish case we had to drop observations below the 5% and above the 95% percentiles of the firm size distribution (EMP) to get a successful matching result. There, and in case 7, we searched only for one control observation.

Table 9 presents the matching results in the German sample. The main diagonal shows the unadjusted shares of patenting firms 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 at the 5% significance level. We do not find a significant effect in Case 2, which considers publicly funded firms compared with non-treated ones. As this is in contrast to the parametric model where public funding is interpreted as an exogenous variable, selectivity seems to produce a large bias if it is not taken into account in the econometric model. Furthermore, we find that firms not currently collaborating nor receiving funding would perform significantly better if they would collaborate (Case 4), or, if they would collaborate and receive funding (Case 10). However, there seems to be no potential benefit from additional funding for individual research (Case 7). Although the effect amounts to 7 percentage points, the t-test does not reject mean equality. This is due to the large number of replicated observations in the control group in this case. Case 5 indicates that publicly funded firms would have performed better if they had collaborated. We do not find other significant effects for the German sample. Hence we conclude that both public funding and collaboration (and the combination of both) leads to improved innovative performance in the economy and there is still potential that could be exploited by setting incentives for collaboration. Increased public funding of individual research does not seem to be promising strategy to foster innovation output.

Table 9: Matching Results for Germany: Average Treatment Effects $E(a^{m,l})$ measured as difference in the probability to patent

		Actual state (m)			
		None	Collaboration	Public funding	Both
Counterfactual state (l)	None	0.386	1) 0.170*** (0.045)	2) 0.076 (0.057)	3) 0.149** (0.055)
	Collaboration	4) -0.132** (0.051)	0.640	5) -0.129** (0.060)	6) -0.047 (0.055)
	Public funding	7) -0.068 (0.067)	8) 0.011 (0.066)	0.598	9) 0.010 (0.064)
	Both	10) -0.158** (0.073)	11) -0.004 (0.065)	12) -0.080 (0.068)	0.732

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 average probability to patent of the groups in columns.

The Finnish data reveals the following effects (see Table 10): first, collaboration and funding (and both) result in increased innovation performance compared with no treatment (Cases 1, 2 and 3). In comparison with the German sample, we find lower additional innovative potential that might be induced by collaboration in the sample of firms that neither collaborate nor receive subsidies (Case 4). As the share of collaborating firms is already much higher than in Germany, it may indeed be the case that a larger proportion of the remaining firms do not show the capabilities needed for successful research. However, Case 12, indicating the group of firms actually receiving public funding, shows that there might be a high additional effect induced by collaboration. As these firms already receive financial means for innovation, this could be better exploited if firms would also collaborate and possibly gain from knowledge spillovers. Therefore, the combination of collaboration and funding promises positive effects, even in the sample of firms not receiving any treatment (Case 10). This may reveal the effect that the Finnish firms are smaller than the German ones, on average, and thus have less access to capital markets to finance innovation activities. Additional capital provided by the Finnish government could compensate for this lack of financing of innovation activities. This hypothesis is also supported by Case 6, showing that firms actually collaborating and receiving funding would exhibit less patenting activity if the government had not decided to subsidize those firms. In this case, firms might not be able to raise enough capital to maintain their high innovation efforts.

Table 10: Matching Results for Finland: Average Treatment Effects E(a [m,l]) measured as difference in the probability to patent

		Actual state (m)			
		None	Collaboration	Public funding	Both
Counterfactual state (l)	None	0.093	1) 0.107*** (0.032)	2) 0.098** (0.045)	3) 0.268*** (0.042)
	Collaboration	4) -0.069** (0.033)	0.220	5) -0.083 (0.057)	6) 0.081* (0.045)
	Public funding	7) -0.080 (0.056)	8) 0.007 (0.069)	0.203	9) 0.127* (0.038)
	Both	10) -0.171*** (0.042)	11) -0.014 (0.040)	12) -0.146*** (0.055)	0.448

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 average probability to patent of the groups in columns.
Note: For the computation of case 8, 9 and 12, we had to drop observations below the 5% and above the 95% percentiles of the firm size distribution (*EMP*) to get a successful matching result. There, and in case 7, we searched only for one control observation.

5 A "quasi" difference-in-difference estimation

Since we observe a high correlation between *LAGPAT* and *PATENT*, it seems intuitive to conduct a difference-in-difference (DiD) estimation as a sensitivity analysis of the results in addition to the matching. DiD is one possibility to control for firm-specific individual effects. However, as *LAGPAT* accounts for the patent activity since 1985, we would clearly underestimate the treatment effects if we compared *PATENT* with *LAGPAT*. Moreover, as stated above, our cross-sectional structure of the data does not allow for a "correct" DiD application, but we can check the following: we construct the variable *PREVPAT* that takes the value 1 if a firm applied for a patent in the period prior to the observation period (not since 1985 like *LAGPAT*). It is zero otherwise. Computing the difference *DIFF=PATENT-PREVPAT* obviously indicates the change in the patenting behaviour over time. In contrast to the matching, this approach controls for firm-specific fixed effects that might contribute to firm performance by differencing them out, and it neither relies on the conditional independence assumption nor is it affected by the common support restriction required in the matching. Note that this approach also rules out possible endogeneity that may affect the matching results due to the inclusion of *RDEMP*.

The DiD estimation performs a before-and-after comparison of treated firms, and compares their change in the patenting activity with the group of untreated firms in order to take into account a possible change in the macroeconomic trend to patent. Note that we call this a "quasi" DiD approach, because we do not observe the treatment status in the previous period as we have only cross-sectional information on that. It is, therefore, likely that we underestimate the treatment effect, because several firms may have received treatment in the previous period too. A few firms that currently belong to the control group may have received treatment previously but did not in the current period. However, with regard to the growing public incentives for innovation, the rising importance of collaboration in industrialized countries and the still considerable size of the control group, we think that this only relates to a small number of cases and causes a small bias, which should play a minor role in the interpretation.

As *DIFF* is a discrete variable taking the values –1, 0 and 1, we estimate a multinomial probit model regressing *DIFF* on the three dummy variables *FUND (only), CO (only)* and *BOTH* including the non-treated firms. This amounts to the DID estimator in a discrete choice framework. We choose a simulated ML estimation using the GHK simulator accounting for possible correlations among decisions. The reference category is *DIFF* = 0. The results are presented in Table 11.

Table 11: Difference in difference estimation (SML using the GHK simulator)

	German Sample (*N* = 1,464)						Finnish Sample (N = 1,520)					
	DIFF = - 1			*DIFF* = +1			*DIFF* = - 1			*DIFF* = +1		
	Coef.		Std. err.	Coef.		Std. err	Coef.		Std. err.	Coef.		Std. err
FUND (only)	-0.220		0.200	0.204		0.133	0.193		0.192	0.518	***	0.165
CO (only)	-0.175		0.149	0.481	***	0.099	-0.263		0.173	0.427	***	0.131
BOTH	-0.028		0.168	0.309	**	0.123	0.129		0.137	0.843	***	0.118
Constant term	-1.511	***	0.065	-1.116		0.053	-1.689	***	0.109	-1.594	***	0.103
LR-Test on RHO = 0	$\chi^2(1)$ = 25.837 ***						$\chi^2(1)$ = 23.903 ***					

Note: *** (**, *) indicates a significance level of 1% (5%, 10%); 200 draws from the simulator.

In Germany the coefficients of *CO* and *BOTH* are significantly different from zero for a change from non-patenting to patenting (see the right column), which implies positive treatment effects for these groups. For publicly funded firms, we cannot support the hypothesis of a positive treatment effect for public funding in this DiD setting. In Finland the estimates show that the treated firms achieve a higher likelihood to change from no patent to at least one patent application. The quasi DiD analysis does largely confirm our previous results for Germany; collaboration has a strong impact on the innovative performance of firms. Pure funding without collaboration does not seem to have a bearing on the firms' patenting behaviour. Also the results of the quasi DiD support the discussion of the Finnish context. Both funding and collaboration individually as well as both in combination excert a positive impact on the innovative output. Finally, it is noteworthy that we also conducted a before-and-after comparison for each treated group separately. This rules out a possible bias of the control group if firms changed from the treated status in the previous period to the untreated group in the current period. This analysis also confirms the findings above.

6 Conclusion

This study focused on the impact of innovation policies and R&D collaboration in Germany and Finland. It started with an overview of the innovation policies and showed that it is interesting to compare these two countries: Germany is the largest economy in the European Union and Finland has been the "shooting star" among the smaller countries in the EU. 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 the innovative output of companies measured by their patenting activity.

Descriptive statistics of our sample reveal that Finland is a pioneer country with respect to the European plans to set public incentives to raise GERD to 3% by 2010; 48% of innovating firms already receive subsidies whereas in Western Germany this figure only amounts to 21%. As R&D collaboration is expected to generate knowledge spillovers and is thus an important factor for the transformation from a resource-based economy to a knowledge economy, Finland performs well too: 64% of firms are engaged in R&D collaborations whereas only 29% do so in Germany. However, we also see that despite an impressive growth of innovation output during the 1990s, the average innovative output measured by the share of firms with at least one patent application is lower in Finland: 28% of innovating firms show at least one patent application; in Germany this share is 44%.

We conducted a treatment effects analysis to assess whether funding and/or collaboration yields a positive benefit in terms of 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 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. This view is also encouraged by other results in the Finnish sample: firms that do not receive any treatment could improve their innovative output if they received both treatments and collaboration in combination with subsidies. From the results of mere collaboration, this could reflect a restricted access to private capital for such a risky undertaking as R&D. In this way, firms that already receive funding but do not collaborate would realize positive benefits from collaboration in combination with subsidies, possibly because they would have sufficient capacity to appropriate knowledge spillovers. Furthermore, we find that firms actually receiving both treatments would perform worse if they had not received subsidies. This acknowledges the hypothesis on capital constraints. Financing constraints in Finland have also been shown by Hyytinnen and Toivanen (2002).

As a further check on our results, we conducted a quasi difference-in-difference estimation. This takes account of firm-specific fixed effects that could not be controlled for in the matching. The results largely confirm those obtained from the matching estimations and show that collaboration in particular significantly contributes to innovative output at the firm level.

Hence the main conclusion of our analysis is that public incentives and collaboration have a positive impact on the treated firms in Finland and, thus, on innovative output. 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.

As further research in this field, it would be useful to have more detailed data on firms' characteristics to investigate if our matching results are also supported with richer information sets. Having panel data to advance with the difference-in-difference estimator would be desirable because it rules out fixed effects possibly affecting the results to some extent. In addition, panel data would enable measuring the relevant covariates before the treatment in order to avoid endogeneity problems. In particular, the conditional difference-in-differences approach (DiD on matched samples) would be an interesting extension of our work.

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