Publicly Funded R&D Collaborations and Patent Outcome in Germany

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Abstract

The stimulation of co-operations and networks has become very popular in R&D policies in recent years. This study examines the development and the impact of publicly funded R&D consortia in Germany. The paper describes the history of R&D funding in Germany with a focus on the development of measures encouraging collaborative R&D activities among firms and public research institutions. Due to a recent shift of policies to more competitive procedures in awarding public funds for R&D, we investigate empirically the impact of such measures on patenting activity at the firm level. The microeconometric results show that collaborating firms are more likely to patent than others. Within the group of collaborating firms, participants in publicly sponsored R&D consortia exhibit a higher probability to patent than firms in non-sponsored networks. Especially SMEs seem to benefit from spillovers which makes their application for patents more likely.

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JEL-Classification: C14, C25, H50, O38

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1 Introduction

Governments in the world emphasize the need to improve the transfer of know-how throughout the innovation system. This means more collaboration between science and industry to strengthen the national innovation capabilities. In most OECD countries public measures are directed to bring private organizations and public research institutions closer together, providing researchers and projects with skills and incentives to take their ideas to the market (cf. OECD, 2002). The main focus of co-operative R&D policies is to exchange expertise among performers, primarily between academic scientists and industrial researchers. Its main objective is to improve the economic contribution of scientists, to improve technological capabilities, and to support innovations and patent activities.

Today's governments search for effective compositions of technology policy instruments, such as fiscal measures, credits or subsidies which are most promising for future growth. "If technological innovation is called the most important force driving economic growth, then public policies designed to promote and encourage technological innovation take on substantial importance" (Branstetter/Sakakibara, 2002). Recently, the European Commission has introduced large networks of excellence in the 6th Framework Programme. Multipartner projects aimed at strengthening the excellence on a research topic by combining resources and expertise. "This expertise will be networked around a joint programme of activities aimed primarily at creating a progressive and lasting integration of the research activities of the network partners, while at the same time advancing knowledge on the topic" (European Commission, 2003). In this line, research and innovation policies have recognised that publicly funded collaborations and R&D networks are promising to strengthen the national competitiveness. Following these discoveries, traditional instruments to stimulate private and public R&D activities have been enlarged by new modes, such as contests and research networks which are characterised by a huge number of partners.

Germany was one of the first countries in Europe which offered intensive co-operative R&D funding in the early 1980s and which introduced co-operative network competitions for public funding in the 1990s. This study tries to shed some light on the reasonable question on the return on that investment: What are the benefits of public incentives for R&D collaborations in terms of innovative output?

In sections the following section we summarize theoretical and empirical perspectives on networks, alliances and partnerships in the innovation process. In section 3, we give an overview on the development and the status-quo of publicly funded R&D co-operations in Germany. Section 4 deals with a microeconometric study on the research productivity (measured by patents) of German firms. We distinguish innovating companies which are not sponsored by the Federal Government and recipient firms of R&D subsidies. Our deeper interest is a comparison of companies which participate in public collaborative R&D projects and firms which collaborate on a privately financed basis. We study whether publicly funded R&D collaborations lead to higher research output than other collaborations.

2 Theory and empirical perspectives on R&D collaborations

The question 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. 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 recently by Branstetter/Sakakibara (2002). Hagedoorn et al. (2000) present a literature review in which they do not only surveyed studies on research partnerships but also take technology policy issues into account. More recently, Link et al. (2002) gives an sensible overview of strategic research partnerships, taking public financial support to firms into account. In Europe, especially in Germany, Austria and France, we actually observe large efforts of R&D policies to link industry-science relationships for a sustainable output in innovation. Huge amounts of government funds are offered to stimulate co-operation in regional and technological R&D networks. The driving force of these European policy activities is to improve competitiveness and to overcome obstacles of growth and unemployment.

Publicly funded R&D co-operations are sponsored to stimulate R&D pacts, because in an intensive technological competition a high-performance research system seems to be necessary precondition for economic success. In the last decade, we observe an increase of the knowledge intensity in production, in market and technological uncertainties, and trends towards specialization in combination with growing technological complexity. Moreover, some kinds of knowledge such as tacit or embedded knowledge can not or just hardly be acquired by market transactions. In times of globalization, the emerging of new media, and of growing research challenges, high-tech competition increasingly requires joint efforts to carry out R&D. Co-operations have obvious advantages, like positive spillovers as well as cost and risk sharing (cf. Audretsch, 2003). Cassiman/Veugelers (2002) explore in an empirical study the effects of knowledge flows on R&D co-operation, highlighting incoming spillovers and appropriability. Their results suggest that incoming spillovers and appropriability have a higher probability of co-operating in R&D. In face of these results the question remains, why firms enter R&D networks and if collaborating firms are successful in terms of innovation productivity?

Hagedoorn et al. (2000) identify three broad categories of explanation why firms enter into research partnerships: (a) transaction cost theory, (b) strategic management theory and (c) industrial organization theory. In transaction cost theory, R&D co-operations are explained as a hybrid form of organization between the market and the hierarchy to facilitate an activity specifically related to the production and dissemination of technical knowledge. Due to the lacking appropriability of R&D, positive external effects are generated. In order to internalize such effects, companies prefer to engage in research collaborations with possible third party users of their research results. In the strategic management theory, research partnerships are explained by a competitive reasons (common defensive position against competitors), by strategic networks (economies of scale and scope), by a resource based view of the firm (to exploit unique capabilities), by dynamic capabilities (to combine competencies) and by strategic options to new technologies (to determine resources for superior future performance). In the industrial organization theory, research collaborations are explained by the existence of market failures due to the perceived public good nature of knowledge. The majority of theoretical studies deal with imperfect appropriable R&D and an increase of market power. Bayona et al. (2001) review similar reasons to explain co-operation: (i) the reduction and sharing of uncertainty and costs, (ii) motivations relating to market access and the search for opportunities, (iii) size and R&D capacity as characteristics of the firms.[1]

The increasing globalization imposes high requirements on the innovativeness of all industrialized countries. This changing environment requires flexible adjustment strategies – not only on part of the business sector. Since the mid 1980s several governments stimulate developments that lead to intensified collaboration among existing organizations. Famous industry-science partnership programs have been designed to enhance the competitiveness of science and industry in the USA (SBIR, ATP, SEMATECH), in Japan (VLSI) and in Europe (ESPRIT, EURECA, CRAFT). In addition most European countries offer national funding schemes to attract R&D collaborations. Especially small and medium sized enterprises (SMEs) often cannot afford in-house R&D. This is where publicly funded research co-operation schemes take effect. Support is provided for firms and public research institutions which jointly implement a research project. Governments stimulate collaborations because R&D consortia are expected to realize spillovers which are seen most important for cost reduction and a higher productivity.

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; Sakakibara, 2001) has analyzed Japanese Government-sponsored R&D consortia over 13 years and has 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 do occur. The magnitude of the effect of the participation in an R&D consortium on firm R&D expenditures is found to be nine percent, on average. Branstetter/Sakakibara (2002) examine the impact of government-sponsored research

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[1] Further theoretical arguments to questions related to research partnerships and well-known scientific representatives are surveyed and/or listed by Vonortas (1997), Hagedoorn et al. (2000), Mothe/Link (2002).

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, relatively to the control firms, is large and statistically significant. Lerner (1999) and Audretsch et al. (2002) evaluate public support of private sector R&D using a broad based-statistical analysis and case-study based investigations of SBIR recipients in the USA. Lerner (1999) supposed, that knowledge spillovers cause particularly large differentials between the private and social benefits from SBIR because spillovers to other firms may be more frequent if applicants involve very early-stage technologies. Audretsch et al. (2002) demonstrates that technological innovation and increasing private sector commercialization derives from Federal R&D. Moreover, their case-study based analyzes show that commercial activity and its attendant spillover effects generate substantial positive net social benefits.

Within literature on science and technology policy, empirical studies usually analyze vertical and horizontal R&D co-operations or formal and informal arrangements. Just a few articles and empirical investigations deal with R&D co-operations as a part of firm's innovative behavior *and* as a policy instrument. Sakakibara (1997) concludes that co-operative R&D has been examined empirically by only a few studies and comprehensive empirical research is almost non-existent. Most treatments have been based on case studies or on the account of a few highly publicized co-operative R&D projects which are not representative.

3 Publicly funded R&D co-operations in Germany

European R&D co-operations originate from technology policy in the 1950s. At this time, when the European economic and technological development was far beyond the USA, governments ask how to catch up in future technologies. Especially the business sector worried about a technological dependence from the USA and feared that Europe may end up as a low level producer in the long run. It was common sense that Europe even runs the risk of being just a consumer of American technologies rather than becoming a competitor. In these times, nuclear power was the most important technology and a chance to become technological independent was a political and industrial model of co-operation among institutions. On March, 25th 1957, Belgium, Germany, France, Italy, Luxembourg and the Netherlands signed the contract of the European Nuclear Community (EURATOM). The target of this community was international co-operation and knowledge transfer in nuclear sciences. This has been the first European approach for specific R&D project networking.

In 1957, Germany brought the "German Nuclear Program" into being, which contained several issues to subsidize R&D in public institutions and in industry. For the planning and carrying out of this program, a nuclear energy committee had been founded, which comprised of experts from academics, industry and politics. This committee was one of the most important science-industry networks until today. The German Government subsidized this partnership to foster national competitiveness by sharing high financial risks in R&D of the domestic industry. In the following years other civilian technology fields, such as research for space sciences, ocean sciences and computer sciences have been added. Since this time, companies and public research institutions are applying for grants to carry out basic science or highly uncertain R&D activities.

When Europe decided to catch up with the technological leadership of the USA at the end of the 1960s, the number of publicly funded R&D areas increased rapidly. Governments offered programs to foster private and public R&D activities in various fields, like ocean and polar research, climate and atmospheric research, research in the service of health, geosciences, building etc. R&D policy was not introduced to promote complex R&D networks, but big science in *individual firms* or *individual public institutions*. For example, in Germany about 5,800 individual R&D projects were sponsored annually in private and public organizations at the end of the 1970s. In this funding atmosphere, big companies were privileged because of their large absorptive capacity in light of their extensive know-how in forward-looking technologies. The three dominant technological funding areas (energy sciences, space sciences, computer sciences) have been considerably enlarged and diversified.

Today, the Federal Ministries of Economics and Labour (BMWA) of Defense (BMVg) and of Education and Research (BMBF) account for almost 90 % of total R&D funds. Federal R&D expenditure on civilian funding areas accounted for around 87 %. The breakdown of R&D expenditure by funding area and funding priority is based on the Federal Government's R&D planning system called "Project Funding Information System" (PROFI). This relation database system contains all information on Government's R&D grants to every project and recipient funded since 1975. It permits an analysis of expenditure in terms of research themes, projects, recipients, funding procedure aso. In the PROFI database the direct project funding in R&D amount to a total of 3,6 billion Euro in 2002. Among 23 large funding areas that are all significant in terms of volume, on an aggregated level identify six most important fields: environment/energy, production/materials, ICT, life sciences, transport/traffic, big science/education and others (cf. BMBF, 2000; Fier, 2002).

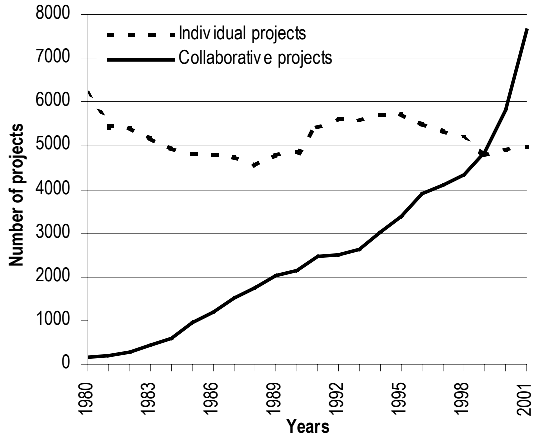
At the beginning of the 1980s, researchers and policy makers have realized that innovative and successful companies rely on alliances, SMEs as subcontractors and intensive co-operations with academics. The success and the exploitation of R&D projects was expected to be more efficient if many partners were involved and for that reason governments were thinking about best practices to stimulate R&D co-operations. Japan was the most popular example of public efforts to foster R&D co-operation, because its hardware industry succeeded in the "Very Large Integration Project" (VLSI) towards the US world market leadership IBM. The success of this project was attributed to temporary alliances of big companies, SMEs, universities and public laboratories. R&D activities of all project partners were financed in a cost sharing between public authorities and private organizations. The first imitator of this R&D collaboration strategy was the USA, which followed with the well known industry co-operation program SEMATECH in 1987 (cf. de la Mothe/Link, 2002).

With respect to international experiences in R&D co-operations, Germany adapted this concept intensely, too. Besides the argument of an important international trend in the field of innovation, critics of a distorting competition caused by individual funded R&D activities has led to the new approach of *collaborative R&D subsidies*. The extensive promotion of R&D in industry has been transformed to the principle of subsidiarity. From now on, German Government's view in the conditions for research promotion in industry were only met in those cases where companies were unable to develop certain technologies on their own – or where they could not do fast enough or not to an adequate extent. To keep the established procedure of R&D project funding, the new co-operative policy instrument was added, but did not substitute individual R&D grants. Figure 1 illustrates this development of R&D policy impressively.

Figure 1:

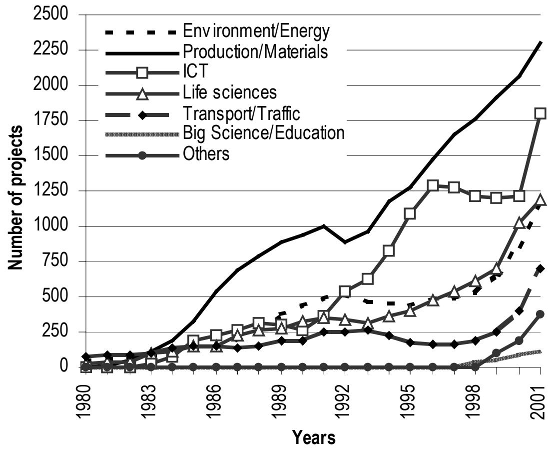
Number of direct R&D funding by the German Federal Government 1980-2001

Number of directly funded individual and collaborative projects



Source: BMBF-Project Database PROFI – Own calculation.

Number of directly funded Collaborative projects by technology priorities



Source: BMBF-Project Database PROFI – Own calculation.

Product engineering and materials research were one of the first technology areas which had been rearranged in their R&D funding procedures from individual to collaborative funding. Several projects of these two funding priorities are very close to industry and applied sciences while other technology fields are more related to basic sciences. Another reason cited for R&D-co-operations is because the competition in these fields of technology have been much higher than in rather monopolistic R&D fields, like nuclear sciences, space sciences or ocean research. With respect to the principle of subsidiarity the German Government changed their funding philosophy towards pre-competitive and co-operative R&D sponsoring. Some years later information and communication technologies (ICT) converted from monopolistic sciences carried out in large multinationals into a broadly used multi-purpose technology. In these times, Government was afraid that a ongoing individual R&D funding may result in similar market distortions as suspected by public sector critics in other funding areas. Because of a huge number of new technology firms which aligned their R&D activities in these technology fields, R&D policymakers reacted immediately and preferred collaborative research projects, too (cf. Fier, 2002).

In the mid nineties, Germany has opened a further chapter in research policy by stimulating *competitive R&D networks*. These new competitive network approaches changed the traditional selection process – in which public authorities fixed the broad field of research – by introducing contests: In a first stage of the funding process, participants set tasks in the framework of well defined technological areas (e.g. biotechnology, mobility in conurbation, nutrition etc.). Afterwards, independent expert jurors identify the best concepts and the most promising solutions. The winners are given the opportunity to submit detailed projects drafts and compete again. At this stage, other potential network-partners such as small and medium enterprises (SMEs) may apply to the winners for inclusion in a project. Today, we can distinguish between regional and thematic contests. Eligible for participation in these contests are industrial enterprises, scientific institutions or public sector institutions which should submit a verifiable and feasible concept for co-operation and the commercialisation of innovative ideas. The winner concepts are funded with an additional amount, but as usual companies and public institutions have to apply for individual or co-operation project grants. Typical contests are regional co-operative contests like “BioRegio” or thematic contests like “Lead Projects” as a specific type of joint R&D pacts. Their purpose is to tackle and achieve forward looking strategic innovation goals by pooling competence in R&D to achieve marketable products, processes and services. Right from the beginning, the research process should be directed towards innovation and a collaboration between researchers and users should be created. In order to attain the given objectives, firms and universities, research institutions and users are requested to form consortia and co-operate in regional and/or thematic networks.

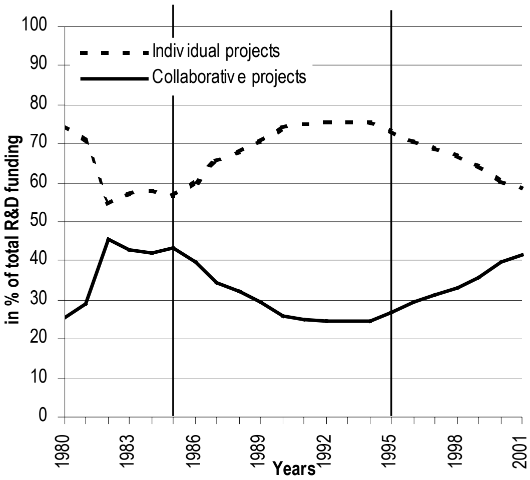
Figure 2 describes the development of the civilian direct R&D funding priorities between 1980 and 2001. At the beginning of the 1980s, we observe a similar distribution of Governments’ subsidies for individual and collaborative R&D projects. This findings corresponds to large investments on R&D in the energy sector. In this time, just a handful well known firm consortia were funded to conduct collaborative R&D, e.g. to build nuclear power stations and to bring these plants into operation. From 1985 to 1994 the annual amounts for R&D in nuclear energy have been reduced dramatically and were partly substituted by projects on renewable energy and energy conservation. In this period, the share of SMEs which were applying for individual grants increased in technologies like ICT, production engineering and materials. Moreover large companies diversified their R&D portfolios and we observe high funding amounts for individual R&D projects. For example, multinational firms whose previous focus had been in nuclear and closely related fields enlarged their scope of research to emerging technologies like application of Microsystems.

In the nineties, R&D co-operations in technologies like ICT and Life Sciences became more significant. In context with "multi-purpose" technologies the number of firms which applied for public grants has grown substantially while the German Government faced R&D budget restrictions at the same time. Due to the conviction of positive impacts of R&D co-operations, the policy orientation changed to foster collaborations among applicants even more. Additionally, it is less expensive and more effective in terms of numbers of potential recipients to subsidize R&D networks in contrast to support single R&D projects. However, individual project funding is still high because of costly R&D projects in space technology, large scale equipment for basic research and marine technology.

Motivated by aspects of globalization another kind of policy instrument came into being in the mid 1990s: the promotion of regional networks. One reason had been that it was impossible to identify something like a German "Silicon Valley", that is a regional cluster of innovative and highly specialized firms in one technology field. Although Germany had a lot of world leading technology firms and public institutions, those are scattered all over the country. The idea of regional networks has been to push the commercialization of research and thus to create successful outstanding centers of excellence, which will be recognized by external investors in the long run.

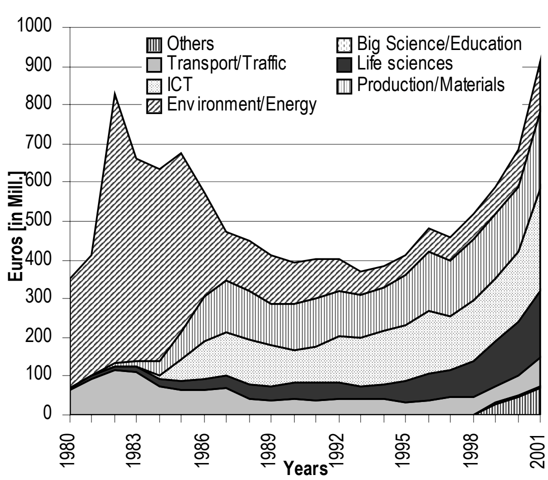
Figure 2:
Total amounts of direct R&D funding by the Federal German Government 1980-2001

Total amounts of directly funded individual and collaborative projects (in %)



Source: BMBF-Project Database PROFI – Own calculations.

Total amounts of directly funded collaborative projects by technology priorities (in Mill. Euro)



Source: BMBF-Project Database PROFI – Own calculation.

Today collaborative R&D projects imply the sharing of resources, usually by project-based groups of scientists and researchers from each involved participant. The type and number of partners is not pre-determined by public authorities. Applicants for direct R&D subsidies are free in their decisions concerning partners, contracts and relationships (c.f. BMBF, 2000 and BMBF, 2003). All partners agree to share their R&D results and the right of use all knowledge generated within the co-operation.

Labor costs, current operating expenditure, expenditure on fixed assets are cost-shared between the partners and the granting institution of the Federal Government.

In Figure 2, we see intensified public investments in R&D collaborations on life sciences. It is based on the first network contest called "BioRegio" in 1995. The contest was initialized to create activity centers on the co-operation of all participants in science, industry and public administration. Regions themselves determine what their focus should be, based on their economic and research activities as well as their qualifications. The three winner regions received an additional project funding of about 75 Mill. Euro (1997-2002). Today, subsequent regional contests like "InnoRegio" are funded with 255 Mill. Euro and encourage people to develop their ability and discover their potential.

In summary, the German Federal Government uses two kinds of project funding to strengthen R&D activities in the economy: (a) *individual project funding* and (b) *collaborative project funding* which is more and more announced in competitions. We have to consider that there are no tax incentives for R&D in Germany, which mean that the direct project funding is currently the most important instrument of R&D policy. It is always provided for a given field of research to achieve an international high level of performance. Network contests and its competitive collaborations are a part of a recent funding philosophy. R&D policy is able to invest its budget more effectively by an increasing number of recipients and by improving its political awareness. Moreover, critics towards market distortions can be rejected because publicly funded technologies are not selected by public authorities, but by science and industry (cf. Fier/Harhoff, 2002).

4 Empirical analysis of patenting behavior

Along with the scientific value and the knowledge acquired, the primary objective of German Research is to make the most effective and efficient commercial use of R&D results. In international statistics the innovative capacity is usually measured by patents (cf. OECD, 1994), for a comprehensive discussion on the use of patents as science and technology indicators). Patents play a key role in the innovation process, not only as an instrument to protect inventions but also as a source of information for the planning an implementation of R&D. Moreover patent indicators are a very important measure for federal governments to classify their country's innovativeness in the international technology competition.

The German Federal Government stimulates the development of patent, licensing and exploitation expertise in their funding procedures. At the time, when a R&D recipient file its application, he already has to submit a plan for the utilization – initially in form of an outline, which subsequently will become more and more detailed. All publicly funded R&D recipients are expected and encouraged to assume responsibility for their exploitation management. Wherever possible, research findings have to be commercially utilized. In order to give an incentive to the grant recipients, the

Federal Government allows to keep all proceeds from the exploitation of patents for at least two years. If the recipient did not apply for a patent within two years, the R&D results become public (BMBF, 2000).

In this section, microeconometric analyses of firms' patenting behavior are conducted. We investigate how different firm characteristics affect the probability to file at least one patent application as well as future patent applications. In principle we distinguish three groups of innovating companies: first, firms that did not participate in any collaborative innovation network. Second, we are able to identify firms which have not received public R&D funding but are involved in R&D co-operations. And third we consider those firms which participate in publicly funded R&D networks from the German Federal Government. If significant spillovers are produced by collaborative research activities, we hypothesize that firms participating in R&D networks will exhibit a higher propensity to patent than other enterprises. We expect, that R&D co-operations shows a higher productivity in terms of patent application due to positive spillover effects. However, it is unclear how publicly funded research networks differ from privately financed collaborations. On one hand, it may be possible that public R&D networks are less productive. It could be the case that the focus on co-operative research of modern public technology policies forces firms to collaborate in order to receive public grants. If the supply of policy schemes would had been different, those firms may well have preferred to keep their knowledge secret and conduct only research projects on their own. In this case, the publicly funded R&D networks will not benefit from spillovers as firms pursue secrecy of their research and do not interact with their research partners involved in the project. On the other hand, the publicly funded networks and the partners involved may exhibit a "higher quality" of the research carried out as the research projects have passed the governmental quality control. Non-public R&D co-operations could have failed in such a process or do only deal with less important research with respect to technological progress.

4.1 Data

In order to perform an empirical analysis as described above, we link company information from three different databases: the Mannheim Innovation Panel (MIP), the Federal Government’s Project Funding Information Database (PROFI) database and patent data from the German Patent Office (DPMA). The MIP is an annual innovation survey which is conducted by the Centre of European Economic Research (ZEW) on behalf of the Federal Ministry of Education and Research since 1993. In 1993, 1997 and 2001, the MIP represents the German part of the European Community Innovation Survey (CIS) of the European Commission. It covers the manufacturing sector and services. The PROFI database used in this study contains information about all public R&D grants of the BMBF and the Federal Ministry of Economics and Labor (BMWA) since 1980. Finally, we extract information on patents from the German Patent Office (DPMA) database which contains the patenting activities in

Germany since 1980. As both the DPMA and the PROFI databases are a census, our sample is determined by the MIP. We use three waves of the MIP, because only those contain a question on R&D co-operations: 1993, 1997 and 2001, i.e. the surveyed information corresponds to the years 1992, 1996 and 2000. Note that the term "innovation panel" is misleading in this case, because we can only perform pooled cross-sectional analyzes. After elimination of data sets with missing values in variables of interest, our sample consists of 4,132 observations referring to 3,568 different innovating firms (see Eurostat/OECD, 1997: 47, for the definition of an innovating firm). About 86% of firms are only observed once in these three selected waves of the MIP.

It is noteworthy that we have excluded a few sectors (on basis of the NACE[2] three digit level) where no firm with participation in an publicly funded R&D network has been present. This avoids unnecessary noise in the subsequent regressions.

4.2 Empirical considerations

The dependent variable in the empirical analysis is a dummy variable PAT_{it} indicating whether the particular firm has filed at least one patent application in recent three years.[3] For about 37% of firm observations *PAT* indicates at least one application. It may be possible that firms utilize their research results later than in the period of the receipt of public funding. The German guidelines on R&D funding lay down that recipients are expected to utilize their research results within a two-year period after completion of the subsidized project. Otherwise the results have to be published to provide the knowledge to other researchers, and the subsidized firms lose their property rights. Due to this incentive, we also investigate future patent applications. The dummy $LEADPAT_{it}$ indicates whether firm i will file at least one patent in year t+1 or t+2. This dummy shows that a share of 23% of firms will file a patent in the next two years. This is consistent with the mean of *PAT* as this covers three years and *LEADPAT* only two.

As described above, the focus of the exogenous variables is basically two dummy variables: from the MIP survey, we use information whether a firm has joint any collaborative R&D project in recent three years. Collaboration 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. By combining this information with the publicly funded research consortia from the PROFI database, we are able to

[2] NACE is the European standard sectoral classification of business activities.

[3] The "recent three years" terminology in the questionaire is common practice in the European CIS. While we can arrange the information from the PROFI and the DPMA database (subsidies and patents) as we like, we have to rely on the structure of the questionnaire in the MIP for several variables. A decomposition into one-year periods is not possible for some measures. Therefore, we merge the databases on basis of the corresponding three year periods.

identify whether a firm has participated at least in one subsidized R&D co-operation or if it has only undertaken privately financed R&D co-operations in recent three years. The share of firms performing collaborative research is almost 40 %, which divides into 31 % of privately financed collaborations and 9 % of subsidized ones. We create the dummy $NFCOL_{it}$ for non-funded collaborations and $SUBCOL_{it}$ for subsidized arrangements. Additionally we include a dummy $SUBSOLE_{it}$ which indicates whether a firm has received grants in a non-collaborative research projects. Four percent of firms have received public grants in individual R&D projects. This prevents a bias stemming from additional funding in solely conducted research.

We use additional control variables to control for firm heterogeneity. Of course, we include firm size measured as the log of the number of employees $LNEMP_{it}$. Since Schumpeter's seminal thoughts about innovation (see Schumpeter, 1934; Schumpeter, 1942), it is indisputable that firm size has an impact on innovative activities, e.g. such as patenting. We also include $LNEMP^2$ to allow for non-(log)linearity. Additionally to firm size, we also include firms' age as explanatory variable. On one hand, with given size very young firms may be more likely to patent because spin-offs from larger firms or research institutions typically involve innovative ideas which are then protected by intellectual property rights. In contrast to this, older firms may show a higher likelihood to patent, because they could have undertaken continuous research which only pays-off after several years of studying and experimenting.

Moreover, the patent stock PS_{it} is computed from the time-series of patent applications in the DPMA data by the perpetual inventory method:

$$PS_{it} = \left(1-\delta\right) PS_{i,t-1} + PA_t \ , \qquad (1)$$

where PA denotes the number of patent applications and δ represents the depreciation rate of knowledge assets and is set to $\delta = 0.15$ (see e.g. Hall (1990). The initial value of PS in 1980 is set to zero. The bias arising from this assumption should be negligible, because the patent data are available since 1980, but the period under review in the regressions starts in 1990. The patent stock controls for the variation of the propensity to patent among firms and enters the regression as lagged value *LAGPS*, that is prior to the corresponding three periods of the dependent variable *PAT*. We divide *LAGPS* by the number of employees to avoid collinearity among regressors. In addition to previous patenting activities, the current potential to patent does clearly depend on the absorptive capacity of firms, i.e. R&D inputs. We measure R&D inputs as the number of R&D employees, divide it by *EMP* to reduce collinearity (share of R&D employees: *SRDEMP)*, and do also include the squared value. 72 % of firms in the sample have at least one R&D employee.

All regressions include a dummy which denotes Eastern German firms as those may behave different due to the still ongoing transformation process of the Eastern German economy. Moreover, 15 sector dummies on basis of the NACE classification should capture different technological opportunities among business sectors. In principle, these dummies are created according to the NACE two-digit sectoral classification. However, some sectors are put together due to a low number of observations. Finally, two time dummies reflects changes in patenting activities over time. See Table 1 for descriptive statistics of the variables and Table 2 for correlations.

Table 1: Descriptive Statistics (4,132 obs.)

Variable	Mean	Std. Dev.	Min.	Max.
PAT	.367	.482	0	1
LEADPAT	.227	.419	0	1
LNEMP	4.896	1.728	1.609	13.010
SRDEMP	0.105	0.209	0	1
PS	0.015	0.044	0	0.484
NFCOL	0.306	0.461	0	1
SUBSOLE	0.044	0.205	0	1
SUBCOL	0.093	0.290	0	1
EAST	0.311	0.463	0	1
LNAGE	2.762	1.226	0	5.278

Table 2: Correlation Matrix (4,132 obs.)

	PAT	*LEADPAT*	*LNEMP*	*SRDEMP*	*LAGPS/ EMP*	*NFCOL*	*SUBSOLE*	*SUBCOL*	*EAST*
LEADPAT	0.42	1.00							
LNEMP	0.38	0.36	1.00						
SRDEMP	0.14	-0.06	-0.18	1.00					
LAGPS/ EMP	0.30	0.23	0.04	0.15	1.00				
NFCOL	0.16	0.11	0.16	0.07	0.02	1.00			
SUBSOLE	0.14	0.09	0.15	0.15	0.09	-0.01	1.00		
SUBCOL	0.24	0.11	0.13	0.23	0.20	-0.21	0.31	1.00	
EAST	-0.22	-0.15	-0.27	0.06	-0.09	-0.01	-0.02	-0.03	1.00
LNAGE	0.25	0.19	0.37	-0.07	0.08	0.02	0.04	0.05	-0.63

There is no collinearity among regressors except between *LNAGE* and *LNEMP* which amount to 0.37. Older firms will naturally maintain more personnel than start-ups or younger firms entering in a phase of expansion. Moreover, *EAST* is negatively correlated with firms' age. This stems from the German re-unification in 1990. Most firms in Eastern Germany have been newly founded when Eastern Germany became a market economy.

4.3 Estimation of Probit Models

We estimate Probit models on the likelihood of at least one patent application and consider a homoscedastic model and a heteroscedastic model. We performed *LM* tests and *LR* tests which show that heteroscedasticity is present (see e.g. Greene, 2000: 829-831). The heteroscedasticity is modeled groupwise multiplicatively with industry dummies, time dummies and firm-size dummies. However, tests have indicated that the use of industry dummies and size dummies suffice. As shown in Table 3, we find interesting results: collaborating firms (see *NFCOL* and *SUBCOL*) exhibit a significantly higher probability to file a patent than non-cooperating firms. Moreover, the coefficient of the dummy indicating subsidized co-operations is even higher than the non-funded co-operations. This may represent a hint that the subsidized collaborations often deal with key technologies which are important for future inventions and firms want to protect their property rights. Non-funded collaborations do possibly deal with less important research topics which do not as frequently generate patentable knowledge as subsidized collaborations. However, it is also possible that the regressions are subject to a self-selection bias. Subsidized firms may substantially be different from other firms that a self selection into subsidized networks occurs. It this case, it is questionable if such firms had applied less likely for a patent if they had not participated in a publicly funded R&D network. Therefore, we take account for a self-selection bias in the following subsection.

Table 3: Probit estimations on patent applications (*PAT*)

	Homoscedastic Probit		Heteroscedastic Probit	
	Coeff.	Std. err.	Coeff.	Std. err.
LNEMP	0.25 ***	0.09	0.55 ***	0.10
LNEMP^2	0.01	0.01	-0.02 ***	0.01
SRDEMP	4.26 ***	0.44	4.26 ***	0.78
SRDEMP^2	-3.43 ***	0.43	-3.62 ***	0.70
LAGPS/EMP	7.08 ***	0.63	7.01 ***	1.14
NFCOL	0.35 ***	0.05	0.26 ***	0.06
SUBSOLE	0.12	0.13	0.04	0.10
SUBCOL	0.59 ***	0.09	0.43 ***	0.10
EAST	-0.35 ***	0.07	-0.33 ***	0.08
LNAGE	0.07 ***	0.03	0.04 *	0.02
Const.	-2.83 ***	0.26	-3.25 ***	0.46
Log-Likelihood	-1,800.56		-1,768.51	
Pseudo R^2	0.337			
# of obs.	4,132		4,132	

Note: *** (**, *) indicate a significance level of 1% (5, 10%)
All estimations include 14 industry dummies and two time dummies. The heteroscedasticity is considered groupwise multiplicatively and is modeled with size and industry dummies.

The other results in Table 3 reveal the expected effects of the control variables. Larger firms are more likely to file a patent. Moreover, the stock of previous patents *LAGPS* is positively significant and firms with a high share of R&D employees exhibit a higher propensity to patent. However, if the share of R&D employees exceeds 60% roughly, the probability to patent decreases. There are some firms in the sample that have a higher share of R&D employees. These are usually small firms in high-tech sectors which may prefer secrecy instead of patenting, because with the patent disclosure their knowledge assets become public, at least partly.[4] Another interesting result is that firms which receive public funding for solely conducted R&D do not show a higher propensity to patent than other firms. This does also point to the hypothesis that collaboration generates positive spillover effects. Firms which receive public funding for R&D have surely passed the "R&D quality control" of the public authorities which have granted the funds. As even such firms show less patent activities than collaborating firms, positive spillover effects seem to be present in such networks.

The regressions on future patent applications reveal the same results as the previous ones. Note that we lose the MIP wave from 2000 for these analysis, because our patent data from the DPMA does not include the years 2001 and 2002. Tests indicate that it is sufficient to include size dummies in the heteroscedasticity term. Although the coefficients between the regressions presented in Table 3 and Table 4 do slightly vary, the statements on the patenting activity remain the same. Collaborating firms, especially publicly funded ones, show a higher propensity to patent even in subsequent two years after the observed period of collaborations. Of course it would be desirable to conduct a long-term time-series analysis, but this is not possible with the available data.

Table 4: Probit estimations on future patent applications (*LEADPAT*)

	Homoscedastic Probit		Heteroscedastic Probit	
	Coeff.	Std. err.	Coeff.	Std. err.
LNEMP	0.79 ***	0.10	0.83 ***	0.07
LNEMP^2	-0.04 ***	0.01	-0.05 ***	0.00
SRDEMP	3.58 ***	0.61	1.61 ***	0.38
SRDEMP^2	-3.36 ***	0.83	-1.67 ***	0.51
LAGPS/EMP	10.53 ***	0.84	8.70 ***	0.80
NFCOL	0.14 **	0.06	0.06 **	0.03
SUBSOLE	0.01	0.15	-0.03	0.06
SUBCOL	0.54 ***	0.12	0.18 ***	0.06
EAST	0.07	0.09	0.04	0.04
LNAGE	0.07 **	0.03	0.03 **	0.01
Const.	-4.29 ***	0.31	-3.64 ***	0.27
Log-Likelihood	-1,326.50		1,287.68	
Pseudo R^2	0.330			
# of obs.	3,331		3,331	

Note: *** (**, *) indicate a significance level of 1% (5, 10%)
All estimations include 14 industry dummies and one time dummies. The heteroscedasticity is considered groupwise multiplicatively and is modeled with size dummies.

[4] Note that patents are published in Europe after 18 months since the (first) application even though patents may not have been granted yet (see e.g. OECD, 1994: 27).

As a test on the robustness of the findings above, we consider the same regressions for a subsample small and medium-sized firms (SMEs) with less than 250 employees. Table 5 and Table 6 show that the results do not change much. Again, tests had indicated that it is sufficient to include size dummies in the heteroscedasticity term.

Table 5: Probit estimations on patent applications (*PAT*):
Small and medium-sized firms with less than 250 employees

	Homoscedastic Probit		Heteroscedastic Probit	
	Coeff.	Std. err.	Coeff.	Std. err.
LNEMP	0,07	0,24	0,36	0,25
LNEMP^2	0,03	0,03	0,00	0,03
SRDEMP	3,80 ***	0,48	3,01 ***	0,47
SRDEMP^2	-2,99 ***	0,47	-2,43 ***	0,43
LAGPS/EMP	6,66 ***	0,71	6,08 ***	0,73
NFCOL	0,30 ***	0,07	0,21 ***	0,06
SUBSOLE	0,15	0,17	0,11	0,13
SUBCOL	0,60 ***	0,12	0,41 ***	0,10
EAST	-0,33 ***	0,08	-0,26 ***	0,07
LNAGE	0,03	0,04	0,01	0,03
Const.	-2,35 ***	0,50	-2,52 ***	0,45
Log-Likelihood	-1,100.98		-1,093.57	
Pseudo R^2	0.259			
# of obs.	2,646		2,646	

Note: *** (**, *) indicate a significance level of 1% (5, 10%)
All estimations include 14 industry dummies and two time dummies. The heteroscedasticity is considered groupwise multiplicatively and is modeled with size dummies.

The impact of the mere firm size vanishes, but the share of R&D employees and the magnitude of the stock of previous patents remain highly significant. The coefficients of collaborations as focus of the analysis are still significantly different from zero. However, the non-funded collaborations are insignificant in the regression on future patent activities. Even for SMEs, the spillovers generated in publicly funded R&D networks seem to be larger than in other co-operative research.

As already pointed out above, the findings may be subject to a self selection bias. As the government follows a "pick-the-winner" strategy, it is questionable if firms had applied for less patents in the case they had not been subsidized. The same may be true for collaborations in general. Firms will also apply "picking the winner" when searching for appropriate partners for joint R&D activities. Therefore, we apply a non-parametric matching procedure in the following subsection which is able to account for selectivity.

Table 6: Probit estimations on future patent applications (*LEADPAT*)
Small and medium-sized firms with less than 250 employees

	Homoscedastic Probit		Heteroscedastic Probit	
	Coeff.	Std. err.	Coeff.	Std. err.
LNEMP	0,60 *	0,35	1,42 ***	0,34
LNEMP^2	-0,02	0,04	-0,12 ***	0,04
SRDEMP	3,52 ***	0,69	2,13 ***	0,58
SRDEMP^2	-3,09 ***	0,90	-1,79 ***	0,66
LAGPS/EMP	8,24 ***	0,88	6,46 ***	0,94
NFCOL	0,08	0,08	0,03	0,05
SUBSOLE	0,03	0,26	-0,05	0,15
SUBCOL	0,54 ***	0,20	0,26 **	0,13
EAST	0,02	0,11	-0,02	0,07
LNAGE	-0,01	0,05	-0,02	0,03
Const.	-3,44 ***	0,73	-4,63 ***	0,65
Log-Likelihood	-703.48		-696.27	
Pseudo R^2	0.229			
# of obs.	2,123		2,123	

Note: *** (**, *) indicate a significance level of 1% (5, 10%)
All estimations include 14 industry dummies and one time dummies. The heteroscedasticity is considered groupwise multiplicatively and is modeled with size dummies.

4.4 Estimation of Treatment Models

4.4.1 Matching and Identification

The matching approach has been developed to identify treatment effects when the available observations on individuals are subject to a selection bias. This typically occurs when participants differ from non-participants in important characteristics (see Heckman et al., 1999; Heckman et al., 1997 for surveys). Popular economic examples are studies on the benefit of active labor market policies.

The matching is able to address directly the question "What would a treated firm with given characteristics have done if it had not been treated?" A treatment in our context is the participation in an R&D network. We will distinguish between collaborating and non-collaborating firms as well as between subsidized and non-subsidized collaborations. The matching estimator balances the sample with respect to the variables included in the matching procedure individually for each observation. The advantage over a parametric regression analysis such as Heckman (1979) famous selection model is that one does neither have to assume a functional form of the equation of interest (the patenting behavior) nor one has to impose distributional assumptions on the relation between the selection equation and the patenting equation. A nice side effect of the matching for empirical applications is that one does not need an excluded variable from the second equation to identify the coefficients as it is usually necessary in selection models. Especially in the context of innovation at the firm level it is always hard to find a variable whose inclusion in the selection equation but the exclusion in the equation of interest is theoretically well justified by an economic model. One disadvantage in comparison to selection models is that the matching takes only account of observable characteristics while the selection models do also allow for selection on unobservables.

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

$$E(\theta) = E(YT \mid S=1) - E(YC \mid S=1) \tag{2}$$

where *YT* is the outcome variable, that is patents in our case. The status *S* refers to the group: *S*=1 is the treatment group and *S*=0 the non-treated firms. *YC* is the potential outcome which had been realized if the treatment group (*S*=1) had not been treated. The problem is obvious: while the outcome of the treated individuals in case of treatment, $E(YT|S=1)$, is directly observable, it is not the case for the counterpart. What would these firms have realized if they had not received the treatment? $E(YC|S=1)$ is a counterfactual situation which is not observable and, therefore, has to be estimated. In the case of matching, this potential outcome is constructed from a control group of non-participants.[5] The matching relies on the intuitively attracting idea to balance the sample of program participants and comparable non-participants. Remaining differences in the outcome variable between both groups are then attributed to the treatment (Heckman et al., 1997).

Initially the counterfactual cannot simply be estimated as average outcome of the non-participants, because $E(YC|S=1) \neq E(YC|S=0)$ due to the possible selection bias. The participant group and non-participant group are expected to differ, except in cases of randomly assigned measures in experimental settings. Rubin (1977) introduced the conditional independence assumption (CIA) to overcome the selection problem, that is, participation and potential outcome are independent for individuals with the same set of exogenous characteristics *X*. If this assumption is valid, it follows that

$$E(YC \mid S=1, X) = E(YC \mid S=0, X) \tag{3}$$

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

$$E(\theta) = E(YT \mid S=1, X=x) - E(YC \mid S=0, X=x) \tag{4}$$

Conditioning on X takes account of the selection bias due to observable differences between participants and non-participants.

4.4.2 Estimation of the counterfactual

A weight w_{ij} is defined with respect to X for each participant i which assignes a high weight to non-participants j being similar in X and vice versa. The weights w_{ij} sum up to one. The treatment effect for participant i is

$$YT_i - \sum_j w_{ij} YC_j \tag{5}$$

The outcome of the treated individual i is compared to the outcome of non-treatment of all non-participants j. According to Heckman et al. (1997) matching estimators differ only with respect to the weights attached to members of the comparison group. The extreme cases are to use all non-treated individuals as control group or to pick just the most similar control observation. The latter case is called nearest neighbor matching. The weight would be equal to one for the most similar control observation and would be zero for all other cases. Nearest neighbor matching has already been applied in industrial economic literature to estimate the impact of R&D subsidies on R&D investment at the firm level (see Czarnitzki, 2001; Czarnitzki/Fier, 2002; Almus/Czarnitzki, 2003).

In this study, a kernel-based matching is applied. In contrast to the nearest neighbor matching where only one control observation is assigned to each participant, the entire group of non-participants is used for every participating individual. Therefore, a non-parametric regression in the sample of non-participants is performed to determine the weights for the potential non-treatment outcome. The weights are specified as

$$\mathrm{w}_{\mathrm{ij}} = \frac{K\left(h^{-1}\left(X_j - X_i\right)\right)}{\sum_j K\left(h^{-1}\left(X_j - X_i\right)\right)} \tag{6}$$

The kernel K downweights observations with respect to their distance to X_i. h is the bandwidth parameter. The weights are obtained by a non-parametric regression that is a locally weighted average of the outcome of the non-treated individuals with similar characteristics. In this case, the Nadaraya-Watson kernel regression is applied. The minimization problem to obtain the non-treatment estimate for individual i is (see Pagan and Ullah, 1999, section 3.2)

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[5] There exist other approaches which are not applicable to our case like a before-after comparison of participants, and a difference-in-difference estimation, where participants and non-participants are compared before and after the treatment (see Heckmann et al., 1999, for example).

$$m(X_i) = \min_m \sum_j \left(YC_j - m\right)^2 K\left(h^{-1}\left(X_j - X_i\right)\right) \tag{7}$$

The resulting estimator equals

$$\sum_{\mathrm{j}} \frac{K\left(h^{-1}\left(X_j - X_i\right)\right)}{\sum_j K\left(h^{-1}\left(X_j - X_i\right)\right)} Y_j = \sum_j w_{ij} Y_j \ . \tag{8}$$

As one often wants to consider more than one matching criterion, one has to deal with the "curse of dimensionality". If we employ a lot of variables in the matching function, it will become difficult to find appropriate controls. Rosenbaum/Rubin (1983) suggested to use a propensity score as a single index and thus to reduce the number of variables included in the matching function to just one. Therefore a probit model is estimated on the collaboration dummy. The estimated propensity scores are subsequently used as matching criterion. Lechner (1998) introduced a modification of the propensity score matching as one often wants to include additional variables, e.g. like firm size, directly in the matching function. In this case, instead of a single *X* (propensity score), other characteristics of the individuals may be employed in the matching function. Therefore the Mahalanobis distance

$$MD_{ij} = \left(X_j - X_i\right)' \Omega^{-1} \left(X_j - X_i\right) \tag{9}$$

is used as argument in the kernel function. **Ω** is the empirical covariance matrix of the vector X_j. Finally, the kernel function and the bandwidth have to be chosen. We use the Gaussian kernel

$$K = \left(\sqrt{2\pi}\right)^{-1} \exp\left(-0.5\left(h^{-1} MD_{ij}\right)^2\right) \tag{10}$$

and the bandwith *h* is chosen according to Silverman's (1986) rule of thumb as

$$h = \begin{cases} 0.9An^{-1/5} & \text{if } \ k = 1 \\ k\left(0.9n^{-1/5}\right)^2 & \text{if } \ k > 1 \end{cases} \tag{11}$$

where *k* is the number of variables included in *X, n* is the number of observations and $A = \min\left(s, iqr/1.34\right)$ with *s* as the standard deviation and *iqr* as the inter-quartile range of *X* in the sample of non-participants (see also Bergemann et al., 2001).

The Nadaraya-Watson kernel regression is performed for every participant in the sample, that is, an estimate of the potential outcome for each *i* is constructed from the entire sample of non-treated individuals. Once the samples have been balanced by the kernel matching procedure, remaining differences in the outcomes are not due to previous heterogeneity in observable characteristics, but can be assigned to the treatment if no selection on unobservables occurs.

4.4.3 Empirical application of the kernel-based matching

We perform two applications of the matching estimator. First, we investigate whether collaborating firms are still more likely to apply for a patent than non-collaborating firms when we consider a possible selection bias. Second, we analyze the group of collaborating firms only, in order to study if the collaborating firms which are publicly subsidized do still show a higher probability to patent than firms which only participate in not publicly funded collaborations.

Initially, we consider a propensity score matching without other variables in the matching function, but we restrict the matched control group to belong to the same industry as the participant. Therefore the weights w_{ij} of potential controls from other sectors are set to zero during the matching procedure.

Table 7 shows the mean values of the considered characteristics of the different firm groups: collaborating firms as "treatment group" and non-collaborating firms as control group. We have 1,646 cooperating firms and 2,486 non-cooperating firms. As the t-tests indicate those firm groups differ significantly in size, in the share of R&D employees, the patent stock and age. Moreover, the sectoral distribution is different (not presented in Table 7). Most important, the groups exhibit different propensity scores on collaboration. As the right column in Table 7 shows, the matching is successful. After the estimation of the control group all differences in exogenous characteristics vanish. However, the patent dummies *PAT* and *LEADPAT* do still differ among groups. Despite controlling for a possible selection bias, collaborating firms are more likely to patent than others, that is we can attribute this circumstance to the fact of collaboration which again supports the hypothesis that positive spillover effects are generated in R&D networks.

Table 7: Mean differences in characteristis of collaborating and non-collaborating firms

Variable	Mean of collaborating firms prior to the matching		Mean of potential control group (all non-collaborating firms)		Mean of control group after the matching procedure	
# of obs.	1,646		2,486		1,646	
	Mean	Std. err	Mean	Std. err	Mean	Std. err
LNEMP	5.36	.045	5.57 ***	.031	5.30	.027
SRDEMP	.16	.006	.07 ***	.003	.16	.006
LAGPS/EMP	.02	.001	.01 ***	.001	.02	.001
EAST	.30	.011	.32	.009	.29	.003
LNAGE	2.83	.030	2.72 ***	.024	2.82	.009
Propensity Score	-.27	.014	-.48 ***	.010	-.044	13
PAT	.54	.012	.25 ***	.009	.38 ***	.005
LEADPAT	.31	.011	.17 ***	.008	.26 ***	.007

Note: *** (**, *) indicate a significance level of 1% (5, 10%) in a two-tailed t-test on equal means of the corresponding group and the collaborating firms.
Mean differences of sectors are not presented. However, the distribution over industries differs prior to the matching but vanishes after the estimation of the control group.

Our second matching approach considers only collaborating firms and we distinguish publicly funded and non-funded co-operations. Our sample contains 384 subsidized firms compared to 1,262 firms which did collaborate but did not receive public grants for this. As Table 8 shows, the groups do again differ prior to the matching, but the differences in explanatory variables vanish after the matching. Once again, the differences in the likelihood to patent (*PAT* and *LEADPAT*) remain significantly.

Table 8: Mean differences in characteristics of collaborating firms: subsidized collaborations versus non-funded collaborations

Variable	Mean of collaborating firms with susidization prior to the matching		Mean of potential control group of collaborating firms without susidization		Mean of control group after the matching procedure	
# of obs.	384		1,262		384	
	Mean	Std. err	Mean	Std. err	Mean	Std. err
LNEMP	5.58	.096	5.30 ***	.050	5.56	.038
SRDEMP	.26	.017	.127 ***	.006	.28	.012
LAGPS/EMP	.04	.003	.02 ***	.001	.04	.002
EAST	.27	.023	.30	.013	.29	.007
LNAGE	2.95	.059	2.78 **	.035	2.97	.016
Propensity Score	-.46	.027	-.94 ***	.014	-.48	.027
PAT	.72	.023	.48 ***	.014	.66 **	.010
LEADPAT	.36	.025	.29 **	.012	.28 ***	.016

Note: *** (**, *) indicate a significance level of 1% (5, 10%) in a two-tailed t-test on mean differences between the corresponding group and the collaborating firms.
Mean differences of sectors are not presented. However, the distribution over industries differs prior to the matching but vanishes after the estimation of the control group.

This evidence points to the fact that R&D collaborations do not only generate spillovers in general, but does also show that there are differences between publicly funded networks and purely privately financed ones. On one hand, it may be more difficult to keep the knowledge produced secret in subsidized networks, because the title and content of the research proposals is available to the public. Therefore, firms will seek to establish their property rights by patent protection immediately. On the other hand, it may be the case that recipients of public grants want to declare that the public investment has led to successful results. First, recipients will almost surely apply for future grants and with prior success they can prove their eligibility. Second recipient firm are forced to patent by the legal framework in the Federal Government's funding conditions (not utilized research results will become a public good two years after completion of the research).

5 Conclusions

When Europe decided to catch up with the technological leadership of the USA, Germany introduced the direct project funding to strengthen the technological competitiveness of nationals' industry. While former project funding was offered as an individual firm's R&D grant, researchers and policy makers realised the benefits of R&D co-operations in the 1980s. In the same time the German Government was criticised because of a subjective allocation of public R&D grants to large firms and because of incurring market distortions. In the mid eighties the German Federal Government added the collaborative R&D funding and switched its funding philosophy for the first time. We do observe impressively an increasing number of collaborative projects, especially in applied technological fields. In the early nineties the R&D funding procedures changed for a second time. Germany opened a further chapter in research policy by stimulating competitive R&D networks. The usual criticised awarding of public funds by Governments' authorities, even in individual R&D projects either in collaborative R&D projects, was added by "contests". In these contests firms and universities, research institutions and users were asked to form R&D networks and to compete among different R&D co-operations and collaborative R&D concepts. Today, the funding of R&D collaboration is an essential element of German Governments R&D funding and most important, because Germany did not offer any R&D tax credits. Our study has focused on the return of investment on that R&D policy shift by analysing the benefits of public incentives for R&D collaborations in terms of innovative output.

In a first step we investigates the benefits of public incentives for R&D collaborations in terms of patents in a microeconometric analysis. We distinguish companies which have been publicly funded in R&D co-operations in comparison to non-funded firms. Our hypothesis is in line with the literature on collaborative research, that spillovers are generated within R&D co-operations. In difference to other empirical studies we use a huge database and distinguish publicly funded R&D co-operations and non-funded co-operations. Comparing these two groups, we find evidence that there are differences between publicly funded networks and purely privately financed ones. We have shown, that firms in publicly funded networks are more likely to apply for a patent than firms in private networks. These findings are supported by Probit regressions on a patent dummy as well as a dummy for future application. Moreover the results do even hold in econometric models which take account of a possible selection bias. We apply a kernel-based matching and compare collaborating and non-collaborating firms as well as collaborating companies which received public grants and firms that did finance R&D cooperation's privately.

The interpretation of our results is twofold: On one hand, it may be more difficult to keep know-how in subsidized networks even secret, because the output is available to all network partners which is synonymous to a public good. In this case, firms seek to establish their property rights by patent protection immediately. On the other hand, it may be the case that recipients of public grants apply their successful result as a patent, to impress their sponsor (Federal Government) as much as their shareholders, competitors etc. Herein recipients of R&D funds take future applications for R&D grants into account and patenting might be a good strategy to convince funding authorities prior to the next application. A third interpretation my result from official requirements: Although patenting or licensing is not conditional, recipient firms are forced to patent by Federal Government's funding conditions.

Finally, it would be useful to distinguish between private-private and public-private partnerships in future research to get more knowledge about the origins of know-how, its transformation into products and processes and thus the efficiency of publicly funded R&D networks.

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