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Abstract

This study investigates the effects of public R&D funding on the funded firms in Finland. It focuses on the input additionality, the output additionality of public funding and the effect an increase of innovation effort has on the innovation output of firms. The data set for this analysis is taken from the Community Innovation Survey which allows us to compare the results obtained with results obtained for other countries. For reasons discussed in the study the Finnish results are checked against results obtained for analyses of the Community Innovation Survey in Germany.

Concerning the overall effects of public funding in Finland we can draw quite positive conclusions based on our empirical analysis: First, on average, public funding increases the private innovation effort of funded firms, in both nominal and real terms. Second, on average, public funding increases the innovation output of funded firms. Public funding yields the largest effects when it stimulating collaborative innovation activities. Finally, an increased private innovation effort increases innovation output on average.

Preface

This report summarizes the results of the research project *Impact of Public R&D Funding* carried out with funding from Tekes (National Technology Agency of Finland) and the Ministry of Trade and Industry under the ProACT umbrella.

The author gratefully acknowledges the financial commitment without which this research could not have been carried out. The author appreciated the efficient management by the program management team and the efforts of Tarmo Lemola in particular.

The author also appreciates the open and inspirational discussions with Tekes' staff. Pekka Pesonen, in particular, offered insightful advice and contributed helpful suggestions. The ProACT program, being an umbrella for several social sciences and economics research projects in the domain of innovation and public policy, offered a rich set of occasions for the exchange of ideas, insights and inspiration.

A large part of the research was carried out while I was with VTT Technology Studies. The excellent research environment there, the great administrative assistance, mainly by Taija Vento, and the open and inspiring atmosphere contributed to the research as much as it contributed to my personal wellbeing. This research would not have been carried out without Torsti Loikkanen's continuous support.

The empirical research was conducted in Statistics Finland's research laboratory, which offered an easy and effective way to access the data. The author highly appreciated the efficient collaboration with Statistics Finland and Satu Nurmi in particular.

An integral part of the research project was a comparison with the impact of public funding in Germany. The collaboration with Dirk Czarnitzki (University of Leuven, Belgium and Center for European Economic Research, Mannheim, Germany) and with Andreas Fier (Center for European Economic Research, Mannheim, Germany) contributed to the success of this research. During the course of this project a number of papers were produced in joint efforts: Czarnitzki and Ebersberger (2005), Czarnitzki, Ebersberger and Fier (2004c), Czarnitzki, Ebersberger, Fier, Hussinger and Müller (2004a), Czarnitzki, Ebersberger, Fier, Hussinger and Müller (2004b), Ebersberger and Fier (2005).

I want to express my deep gratitude to Dirk Czarnitzki who introduced me to the art of microeconometric matching.

Last but not least I am extremely grateful to Sabine Köntopp for her enduring support.

Karlsruhe, September 2005

Bernd Ebersberger

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Executive summary

This study investigates the input additionality and the output additionality effects of the Finnish government's intervention in private sector innovation activities.

Research question

Since R&D and innovation activity is a main driving force for economic growth, it is important to ensure that it occurs at an optimal level. Without governmental intervention we expect an underprovision of R&D and innovation activity. Companies cannot completely exclude competitors from using their results. Because companies realize the appropriation problem, they engage in research less than would be optimal. Governments therefore intervene by investing directly in R&D activities (e.g. expenditures for higher education) and by employing tax credits and grants as incentive mechanisms to raise private innovation activity.

An analysis of the effects of public intervention is warranted for reasons of accountability and transparency. R&D subsidies should only be used if they indeed increase private R&D spending. This condition is necessary but not sufficient. In order to justify R&D subsidies one should also require that the potentially increased innovation activity (input additionality) eventually translates into increasing innovation output (output additionality).

The research questions tackled in this research are as follows:

(1) Does governmental intervention in the shape of public subsidies for innovation increase the input into innovation? In particular, does it increase the private input into innovation?

(2) Do public subsidies for innovation raise the innovation output?

(3) Does the increase in innovation input determine the improvements in innovation output?

By and large the literature provides evidence for positive effects of public funding on both innovation input such as innovation expenditure and innovation output in term of patenting. However, research on the effect of public intervention on innovation output is less developed than it is for the effect on innovation input. In addition the international comparability of the studies is rather underdeveloped. Finally, no internationally comparable analysis has been carried out for the impact of public funding in Finland. As Finland and Germany have in common a comparable national innovation and R&D policy, a comparable set of policy instruments aimed at stimulating business R&D and a comparable public funding system, we use Germany and the impact of public R&D funding for detailed comparisons. Despite these commonalties both countries experienced different success in terms of technological and economic development. The analysis here is not aimed at explaining the differential performance of the Finnish and German innovation systems. Rather we argue that, despite the different performance, Finnish and German funding schemes and their effects can be compared.

Methodology

Methodologically we can potentially use four different approaches to estimate the effect of public funding: instrumental variables (IV) approaches, difference in difference estimators, selection models, and matching approaches.

The IV estimator is found to be unsuitable for the research questions posed in this research. All other approaches have their advantages as well as their shortcomings. In the following sections we will base our main arguments on empirical findings which we obtain by employing the matching estimator. There, governmental intervention is interpreted as a treatment. For each treated firm the matching analysis finds a non-treated company which is comparable to the treated one. The difference in the behavior of the treated and non-treated firms is an estimate for the impact of the treatment.

However, we will not restrain ourselves to the application of a single methodology. We will supplement our analysis of the input additionality with Heckman selection models. The analysis of the output additionality will be augmented by a variant of the diffs-in-diffs estimator.

Data

The data basis for this analysis is the Community Innovation Survey (CIS). The CIS surveys collect firm-level data on innovation across member states by means of largely harmonized questionnaires. Thus the data are comparable on the European scale and are based on a representative sample of companies within each economy. In this analysis we use the second and third waves of the Community Innovation Survey (CIS II and CIS III) covering the years 1994 to 1996 in the case of CIS II, and 1998 to 2000 in the case of CIS III. The Community Innovation Survey closely reflects the definitions brought forth in the Oslo Manual and thus provides a good coverage of the indicators capturing innovation input and innovation output.

Although CIS data contain an abundance of indicators to measure the effect of governmental intervention we restrict the analysis to two essential categories covering the input and output dimensions. We analyze the effect of governmental intervention on innovation expenditure and on patenting activity. The data for the empirical analysis are supplemented by data from other sources where necessary.

Input additionality effects

The analyses show that public subsidies induce Finnish firms to spend more on innovation than they would without the subsidies. Public funding exhibits a strong input additionality effect.

From the analyses we exclude complete or partial crowding out. The results suggest complementarity of public funding and private innovation expenditure. The results are in line with the findings for a comparable set of German companies. The size of the effect is comparable to that shown in the analysis of the German sample. Heckman selection models obtain quantitatively similar results, suggesting that the assumptions underlying the matching approach are not grossly violated.

The reasons for this remarkable input additionality can be explained by determinants within the subsidized firm, by determinants outside the subsidized firm and in the decision principals of the funding agency. Within the firm the receipt of public subsidies has a strong bearing on company internal arguments in favor of the funded project. A positive funding decision may not only shift the priorities between potential R&D projects, which would not result in any additionality, but also shift the priorities in relation to projects unrelated to R&D. This shift causes increasing innovation intensity as a result of the decision to provide public funding. This line of reasoning may be especially relevant for larger firms.

Factors in the business environment may affect the additionality of public funding for small and medium sized enterprises in particular. Imperfections in the financial markets expose SMEs to financial constraints on innovation activities. Public funding may be a means of alleviating these financing constraints. The fact that SMEs in particular benefit from the subsidies supports the idea that public R&D subsidies work as leverage for SMEs to tap into other sources of financing. Receiving a public R&D grant can serve as a quality indicator of the firm's R&D efforts. This may reduce the threshold especially for SMEs to acquire more funding for their innovation efforts from the financial markets. We also observe that increased nominal input in R&D – R&D expenditure – translates into increased real input in R&D – R&D personnel.

Output additionality effects

The analyses show that, in the sample of Finnish firms, considerable output effects are realized by public subsidies for innovation activities.

At the same time we are able to distinguish the effects generated by collaboration from the impact of public funding. As far as was permitted by the available cross section data, we checked the robustness of the results by using a quasi-difference-in-difference estimation which – at least partially – controls for firm-specific effects. The quasi-diffs-in-diffs estimation confirmed the results obtained by applying the matching approach.

For our sample of Finnish firms, we find that higher innovation output is induced by collaboration, public funding and both of them together. Collaboration adds to the effects of public subsidies, while public funding increases the output of firms already engaged in collaborative innovation activities.

The fact that the actual receipt of public funding has a positive effect on both collaborating and non-collaborating firms suggests that financial constraints on innovation activities are overcome or smoothed by the subsidies, which translates into increased innovation output.

For the Finnish sample we also find that collaboration exerts a positive effect on the innovation output of funded and non-funded companies, supporting the idea that incentives for collaboration within the funding schemes increase the innovative output and effect of funding.

Relationship of input additionality and output additionality

For all observations, private innovation expenditure and additional innovation expenditure both have a significantly positive effect on a firm's patenting probability. Both effects do not differ in size. For the sub-sample of SMEs, we also find that private innovation expenditure and the additional innovation expenditure induced by public funding have a positive effect. However, the marginal effect of the latter on patenting probability is significantly larger than the marginal effect of the former. It is twice as large. Since SMEs are notorious for being financially constrained, we interpret this result as showing that public subsidies push SMEs over a threshold for financing R&D. These subsidies leverage an additionality effect which allows SMEs to yield increasing returns on their innovation activities.

Overall assessment

Concerning the overall effects of public funding in Finland we can draw quite positive conclusions based on our empirical analysis.

(1) On average, public funding increases the private innovation effort of the funded firms, in both nominal and real terms.

(2) On average, public funding increases the innovation output of the funded firms. Public funding yields the largest effects when it stimulates collaborative innovation activities.

(3) On average, an increased private innovation effort increases innovation output.

One policy option which we have identified in the analysis of section 6 is that, on average, positive effects could be yielded by inducing voluntary collaboration. However, if we bear in mind that, by international standards, the collaboration density is rather high in the Finnish innovation system, there may be limits to increasing the propensity to collaborate in innovation. Funding for the collaborative R&D of companies that are not yet actively collaborating may be an option to increase the innovative output.

Although we find positive effects of funding regardless of the collaboration status, the analysis suggests that, on average, handing out funding to as yet unfunded companies will not result in an increase in innovation output, if it does not induce non-collaborating firms to engage in collaboration for innovation. We also expect no effects from extending funding to companies that are already engaged in collaborative R&D.

1. Introduction

_______ *This section puts the study into context, clarifies the research questions and shows the structure of the study as whole, giving an overview of what is to come.* _______________________________

This study is about governmental intervention into private sector innovation activities. Its core question is whether or not scarce governmental funds have been used in an effective way to foster innovation in Finland.

In Lisbon in March 2000, the EU Heads of States and Governments agreed to make the EU *the most competitive and dynamic knowledge-driven economy by 2010*. This aim is split up into several target areas: (1) an information society for all, (2) establishing a European area of research and innovation, (3) creating a friendly environment for starting up and developing innovative businesses, especially SMEs, (4) economic reforms for a complete and fully operational internal market, (5) efficient and integrated financial markets, and (6) coordinating macro-economic policies (fiscal consolidation, quality and sustainability of public finances). Although the overall agenda has experienced a modification denoted as a new start for the Lisbon strategy, innovation remains at the core of the strategy: "The realization of a knowledge society, based upon human capital, education, research and innovation policies, is key to boost our growth potential and prepare the future." (European Commission 2005, p. 5.)

The approach to implementation – referred to as the Open Method of Coordination – can be seen as an organizational innovation itself. It rests on common guidelines, which are measured by common indicators to single out best practices, adjust national action plans and monitor the results (Thiel 2005, Kotz 2005). To operationalize the innovation target the expenditure on R&D should be increased from 1.9 percent to 3.0 percent of GDP in the European Union and in all member states by 2010, and the share spent by the business sector should rise to two-thirds of the total expenditure (European Commission 2003). By 2002 Finland had already fulfilled this target.

In none of the member states – and especially not in Finland – did innovation appear on the policy agenda only in the wake of the Lisbon strategy. As Lemola (2002, 2004) shows, technology and innovation found its way into Finnish policy making more than three decades ago as part of the Finnish modernization project. Although it started late compared to other developed OECD countries, Finland caught up due to the quick development of science and technology policy. The general trend among OECD countries towards increasing support for industrial innovation in the late 1970s was also adopted in Finland. Institutional and organizational changes such as the founding of Tekes (the National

Technology Agency) in 1983 facilitated support for industrial innovation. The strengthening of industrial innovation through science and technology policy clearly replaced science with its social objectives by technology, with innovation and competitiveness as its main objectives.

1.1 Research questions

Innovation is an essential ingredient of sustainable competitiveness. An essential part of innovation is the framework of public policy and policy intervention itself (Georghiou et al. 2003). The focus of this study will be the impact of public intervention on the private sector's innovation activities. The underlying line of reasoning of the Lisbon strategy is inherently supply-side-driven and input-oriented. It consists of a set of subsequent hypotheses. First, increasing inputs into research and technological development will increase Europe's capabilities to innovate. Second, these increased capabilities will lead to an increased number of new processes, products and services which will eventually trigger increases in productivity, growth and employment.

Anticipating the discussion below, we will merely focus on public subsidies as a measure of governmental intervention. As governmental intervention in innovation directly targets the R&D activities of funded firms, we can evaluate the impact of the funding along a hypothetical linear innovation path:

(1) Does governmental intervention in the shape of public subsidies for innovation increase the input into innovation? In particular, does it increase the private input into innovation?

(2) Do public subsidies for innovation raise the innovation output?

The first research question asks about the *input additionality* of public funding[1] whereas the second research question looks at the *output additionality* of public funding. If both research questions are answered positively, we can extend to a

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[1] In terms of the Lisbon strategy: If public funding increases private spending on innovation, it can work as leverage to gear the structure of the innovation input towards a two-thirds input from industry.

third research question which focuses on the relationship between the increase in input and output:

(3) Does the increase in innovation input determine the improvements in innovation output?

Essentially the third research question tries to validate the hypotheses underlying the Lisbon strategy in the Finnish context.

The focus on the effects of the subsidy, coupled with the lack of attention paid to the resources spent on intervention, puts effectiveness rather than efficiency at center stage of the study. Hence, the results are much more a cost-effectiveness analysis than they are a cost-benefit analysis.

1.2 Methods and approach

The study will mainly rely on econometric methodologies to assess the impact of public funding on the innovation input and the innovation output. Most of the analysis will rest on the matching approach to identify the impact of public subsidies. In addition to the matching approach we will also employ selection models and a modified diffs-in-diffs estimator to check the sensitivity of our results to the strong assumptions of the matching approach. Generally the econometric analysis is carried out at the firm level.

Although the core focus of the study is the impact of public R&D funding in Finland we will closely compare the results obtained here with the results obtained in the literature. Because of its similarity in the structure and organization of governmental intervention in innovation, Germany is used as a particular country of comparison. To facilitate international comparison this study relies on the Community Innovation Survey for the most prominent internationally comparable data on firm-level innovation activities.

The study focuses only on the microeconomic effects of public funding. It does not dare to aggregate the microeconomic effects into macroeconomic effects and tempt the reader to draw inferences about the efficiency or the cost-benefit ratio of public funding. The overall result of an aggregation of micro effects to form a macro level depends on the weights attributed to the success of one firm and the weights attributed to the failure of another. We believe that, in this light, the aggregation of the effects of public funding on R&D is subject to the well-known impossibility theorem of aggregation introduced by Arrow (1951).

What can be done, however, is to analyze not a single statistic of the effects, but to give an image of the whole distribution of the effects on the population of firms.[2]

1.3 Structure of the study

After this introduction the study discusses the theory behind the justification of public intervention in private innovation activities. Section 2 also introduces potential instruments for governmental intervention. The aim of this study, which is to investigate the effects of governmental intervention, requires a discussion on how governmental intervention can be measured empirically and what indicators could potentially be used to depict the effects on innovation. Finally, section 2 briefly introduces the literature on the impact of public subsidies for R&D.

Section 3 highlights the general trends with respect to innovation policy in Finland and Germany to set the stage for the comparative analysis in the following sections. It also gives an overview of the performance of the national innovation system between the early 1990s and the early 2000s. In section 4 we first introduce the data used in the assessment of the effects of public R&D subsidies. Then we discuss the microeconometric methodologies used to assess the impact of public subsidies. The discussion includes an instrumental variable estimation, the difference-in-difference approach, selection models and matching. Only the latter three will be shown to be suitable for our empirical analysis.

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[2] In section 5.7 below we argue along these lines and refer to an as yet unpublished work that investigates the distribution of the impacts of public funding on the whole population of firms.

Sections 5, 6 and 7 cover the empirical analysis. Section 5 is an empirical analysis of the effects of public subsidies on the innovation input of subsidized firms. After an extensive exploratory analysis the matching approach is used to assess the impacts of public funding on the R&D expenditure of funded firms in Finland. Two different assumptions will be analyzed, giving rise to an upper and lower boundary of the effect. Studies for German samples of firms are compared to with the results obtained here. Finally the sensitivity of the results to the choice of methodology is checked by employing selection models to estimate the impact. In section 6 we investigate the impact of public funding and collaboration on the innovation output of companies. The particular setup of the analysis can assess the mean effect of the actual policies. In addition, it can also highlight the mean effects of potential policy changes and policy options. The analysis includes an identical analysis for a sample of German firms which facilitates close comparison of the results. Section 7 concludes the analysis by summarizing the findings of the previous section. It not only recapitulates the findings, but adds an important step in the empirical analysis. After finding positive input additionality effects and output additionality effects the analysis ties together the findings from section 5 to the findings from section 6. It answers the third research question.

2. Theoretical background and literature review

This section discusses the theoretical background and reviews the empirical literature. It presents theoretical considerations which justify governmental intervention in innovation. It discusses the instruments by which the government can intervene and how intervention and its effects can be measured empirically. Finally, it presents the empirical literature in which macroeconomic studies are differentiated from microeconomic analysis.[3]

[3] Parts of this section are based on Czarnitzki et al. (2004a).

2.1 Introduction

The central object of this research is to assess or evaluate the impacts of public R&D subsidies. These constitute governmental intervention in private business activity, and specifically in private innovation activity. This section will briefly sketch the arguments justifying public intervention. This does not reflect an irrevocable view on our part that market coordination of private business activity yields the best results, and hence any governmental intervention in the market process requires justification. Rather it reflects our belief that governmental intervention – especially in areas with issues that defy short-term solution – follows a different rationale which is neither superior to nor inferior to the economic rationale of the market place. Yet, because this analysis will be entirely an economic and econometric analysis, we do not allude to that different rationale. Rather we emphasize, by sketching the theoretical arguments for governmental intervention, that the market – measured by its own standards – fails to achieve the best possible solutions to problems of technological development and that governmental intervention offers one solution to improve on sub-optimal market results. Subsequently, we discuss tax incentives and R&D subsidies as measures that can be employed to induce the private business sector to increase innovation activity.

To be able to assess governmental intervention and its effects, we elaborate on a plethora of indicators for intervention and its effects on the innovation activities of the private business sector. Subsequently, only two of them will be used in the empirical analysis. A brief ramble through the empirical literature puts the empirical analysis into its scientific context.

2.2 Justification for public intervention

The fundamental rationale for governmental intervention in economic activities derives from market failure. This rationale also applies to governmental intervention in R&D. Hauknes and Nordgren (1999) mention that governmental intervention in innovation-related activities is justified by the market failure argument as well as by the fulfillment of governmental and public needs concerning health, the environment and defense. However, as governmental intervention in the fields of health, the environment and defense can also be justified by the market failure argument (cf. e.g. Frisch et al. 2001), the overall argument for governmental intervention is market failure.

Given that there is indeed market failure in the context of R&D and innovation, it can serve as a justification for governmental intervention. However this does not explain why governments indeed intervene. This question can only be answered by analyzing the political sphere and the decision-making process within the government and its bodies (cf. e.g. Blankart 2005). This question will not be tackled in this analysis; rather do we give an account of the most prominent arguments on which an economic rationale for governmental intervention in R&D and innovation can be built.

Generally the notion of market failure characterizes a situation in which the market's inherent coordination mechanism fails to allocate goods and resources in an efficient way. In this context efficiency refers to the concept of Pareto-efficiency. Pareto efficiency is achieved though a perfectly competitive market, which requires quite a number of conditions to be met: (1) Perfect competition. Perfect competition excludes the possibility of any of the players on the market having market power. Essentially this means that each single player – in order to optimize his or her outcome – has to take the price of a certain good or resource as a given. (2) No externalities. Economic interaction only affects the buyer and the seller. No third party is affected outside the market interaction. (3) Property rights. Property rights need to be strictly defined. (4) Exclusive. Property rights guarantee that actors with no right to use a commodity can be excluded from doing so. (5) Transferability of property rights. Property rights need to be tradable. (6) Perfect rationality of the actors, no asymmetric distribution of information across actors.

Various features can lead to markets losing the power to yield efficient results. In the following discussion we briefly discuss these features and their relevance for innovation.

Generally, public goods are characterized by non-excludability and non-rivalry in consumption. Non-excludability means that it is technically impossible (or prohibitively expensive) to prevent actors from consuming the good. Non-rivalry in consumption is the phenomenon in which one actor consuming the commodity does not diminish the benefit for other consumers of the same commodity. Knowledge – seen as an essential input in generating innovations – has some public good characteristics. Once created, it can be utilized not only by the creator who has borne all the costs of creation, but also by companies not involved in the creation process.

Knowledge spills over between its creator and other actors who, limited by their own capabilities (Cohen and Levinthal 1989; 1990), can utilize the knowledge. This creates an appropriability problem for the creator of the knowledge. Innovators and inventors cannot fully appropriate the returns of their innovation, because competitors may imitate it. Hence, from a social point of view, firms will under-invest in knowledge and knowledge-creating processes such as R&D and innovation activities in general (Nelson 1959, Arrow 1962). From an incentive point of view, firms will seek complete protection of their created knowledge. This will also lead to a suboptimal situation as resources will be wasted in duplication of research.

Collaboration for innovation and research joint ventures are a means for companies to manage the non-rivalrous nature of knowledge and the associated appropriability problems. The question of how and why firms engage in collaborations, partnerships, alliances, joint ventures and networks emerged during the 1980s in economic literature. Various theories and empirical studies analyzed the mechanisms within research consortia and their benefits. Important contributions are Katz (1986), d'Aspremont and Jacquemin (1988), Freeman (1991), Kamien et al. (1992), Katsoulacos and Ulph (1998), Robertson and Gatignon (1998), Kamien and Zang (2000), and Cassiman and Veugelers (2002). Link et al. (2002) and Hagedoorn et al. (2000) give overviews of strategic research partnerships, taking public financial support for firms into account. As the perceived disadvantages of collaboration may outweigh the expected private return on collaboration, a suboptimal level of collaboration and knowledge sharing may result. Fruitful collaboration for innovation requires a firm to possess a distinct set of capabilities. The success of cooperative R&D may fall short of what it could be, if these capabilities are not present. These considerations justify governmental intervention to increase the capabilities to collaborate for innovation and to raise the incentives to do so. Georghiou et al. (2003) mention the policy of the Finnish National Technology Agency (Tekes) that large companies will more likely receive funding if they collaborate with SMEs.

This effect of underinvestment is even more prevalent, as knowledge acquisition and knowledge creation is subject to large sunk costs which create a strong barrier to entry.[4] An additional and related argument in favor of governmental intervention is that the financial market may fail to provide appropriate financing for innovative activities. Several features contribute here. The endeavor is not only risky; it is inherently uncertain, as no success probabilities are known for some types of innovative project. In this case, the financial markets cannot supply appropriate financing. In addition, the size of some innovation projects and the associated risks are beyond what a single firm or private actor is capable of and willing to take. Even if there is suitable financing in the capital market, the cost of searching for it may be prohibitively high for individual firms. There is also the problem of asymmetric information in which the financing bank, venture capitalist or agency has less information about the success potential of a potential innovation project. The screening of projects and project applicants is a costly process. However, asymmetric information does not call for governmental intervention as long as we cannot argue that the information will be less asymmetric if the government intervenes.

2.3 Instruments for governmental intervention

A market failure resulting in underprovision of R&D provides the rationale for governmental intervention. The aim is to raise R&D expenditure to a socially optimal level by the use of adequate instruments. There are principally two instruments that are commonly employed:

(1) tax incentives

(2) grants.

Both are market-compatible in that they aim to induce a change in behavior, rather than commanding it.

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[4] The non-rivalry of knowledge or information use and the sunk costs are an argument in favor of government intervention, even if we abandon the demanding and unrealistic benchmark of pareto-efficiency and employ interim-efficiency of markets instead (Holmström and Myerson 1983; Georghiou et al. 2003).

2.3.1 Tax incentives

Tax incentives reduce the cost of R&D activity and therefore encourage companies to invest more in innovation-related activities. It is possible to grant an immediate write-off of R&D-related expenses, to give R&D tax credits or to allow an accelerated depreciation of R&D-related investment. Tax incentives do not discriminate between R&D projects – they are available for any R&D activity.

2.3.2 Grants

Grants usually match private R&D expenditure at a certain percentage (matching grants). The government or funding agency can select specific projects, for example those from which it expects large spill-over effects. Grants allow the government to influence the investment behavior of companies in a more targeted way. It can therefore be an efficient instrument to implement specific objectives.

The focal point in analyzing the effects of grants is their efficacy. Since the aim of governmental intervention is to *increase* private R&D expenditure, it is necessary to investigate whether the public money is really spent on *additional* R&D activities. Do funded companies commence R&D projects that they would not have carried out otherwise? The risk of R&D subsidies is that companies may reduce their own contribution to R&D once they receive the subsidies. Governmental intervention is only successful, if companies that previously did not engage in R&D activities start to innovate or, if R&D performers increase their private R&D budget.

A major task of economic policy analysis therefore is to test whether public subsidies increase private R&D spending. Phrased differently, the aim is to find out whether public subsidies are a complement or a substitute for private R&D expenditure. To clarify the notions it is useful to differentiate between *total* and *net R&D* spending at the company level:

(1) *Total* R&D spending is the sum of private R&D spending (financed exclusively by the company) and public R&D subsidy.

(2) *Net* R&D spending is only the privately financed part of total R&D spending.

If a public subsidy increases net R&D spending, then a relationship of *complementarity* is found as it increases the subsidized firm's own R&D expenditure. We can be confident that new R&D projects have been undertaken or that existing R&D projects have been enlarged, if the increase in net R&D spending has not been offset by wage and salary increases among R&D employees. On the other hand, if a public subsidy reduces net R&D spending, then a relationship of *substitutability* is established (cf. David et al. 2000). Companies reduce their own contribution to R&D as a response to the subsidy.

It is not always possible to differentiate between complementarity and substitutability in empirical studies. In order to do so, the analyst needs to observe the *size* of the subsidy. If it is only possible to observe whether a company receives a subsidy or not, we cannot calculate the privately financed part of total R&D spending. If it is therefore found that public money increases *total* R&D spending, it can only be concluded that there is *no total crowding out*. Total crowding out would mean a one-for-one substitution of public for private money.

Even if we can establish that R&D subsidies are successful in increasing R&D activity, this is still no evidence that increased R&D effort leads to improvements in innovation output.

2.3.3 Summary

As stated above, both tax incentives and grants are compatible with the market logic, as they give an incentive for behavioral change by influencing firms' economic rationale rather than by forcing the change. They achieve their aim by changing relative prices in favor of R&D, making it cheaper and hence more attractive to carry out. If it is combined with other restrictions or incentives, such as the above-mentioned incentive for cooperative R&D, the grant will also affect the expected output and outcome of the subsidized innovation activity.

Hence, grants and tax incentives for innovation activities not only attempt to affect underinvestment in R&D (which has a clear focus on innovation input), but also try to affect innovation output and outcome.[5] There will be a welfare-enhancing effect only if increased innovation input triggers higher innovation output and outcome. An important task in testing the efficacy of public subsidies is to measure the R&D output that is achieved by public subsidies.

2.4 Measuring public intervention and the impact of public intervention

Public activity in the area of R&D can be discussed from two perspectives. First, public intervention can be analyzed by the magnitude of the related expenditure. This includes a discussion of the public sector's direct R&D expenditure, such as expenditure on higher education or civilian and non-civilian R&D. It also includes the above-mentioned government instruments that aim at raising R&D activity in the private sector, i.e. tax credits and matching grants.

However, an analysis focusing only on the expenditure dimension of public intervention does not shed light on the generated effects. Hence, the second perspective takes account of the effects that public intervention generates with respect to other economic actors. The effects accrue through influencing the private sector's innovation activities. Here we consider the additional R&D activity (R&D expenditure and innovation expenditure) that is induced in the private sector and the output and outcome, such as patents, new products and labor productivity.

Before discussing the measurement of public intervention and its effects we briefly highlight two features of measuring the impact of public innovation intervention that must be confronted in the empirical analysis.

[5] See Table 2-4 in section 2.4.1.4 on page 40 for an example of a tax incentive which also induces collaboration for innovation.

Endogeneity

A major challenge for microeconomic studies is the endogeneity of firms' decisions to participate in government support programs. Neither the decision to apply for a grant, nor the probability of receiving a grant, is independent of company characteristics. If the decisions of firms and the government were random, it would be possible to simply compare the R&D expenditure of supported and non-supported companies in order to calculate the subsidy's effect. However, it is likely that supported and non-supported companies differ systematically. For example, companies with particularly good research ideas may apply for funds, or the government may choose to support companies that have R&D projects with limited risk and a high probability of success. We can also think of endogeneity in the reverse direction. Some characteristics of firms – such as being an R&D performer – are endogenous to receiving funding.[6]

Heterogeneity

Another important problem comes with the heterogeneity of companies. One would expect that companies would differ in their reaction to R&D subsidies. Company size could be influential, for example. The research organizations of large companies are more sophisticated. They have access to more resources than small companies. Furthermore, technological capabilities differ according to the sector in which the company is active. One can hypothesize that the heterogeneity of firms results in heterogeneous effects from governmental intervention.[7]

2.4.1 Measurement of governmental intervention in innovation

The following sections discuss the measurement of governmental intervention in innovation, e.g. with respect to public sector R&D, R&D performed by the

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[6] We will come back to this feature in section 5.4.

[7] This case will be referred to as the case of heterogeneous treatment effects and will be discussed in section 4.3.1.2.

higher education sector, civilian and non-civilian R&D, and finally tax incentives and R&D subsidies.

2.4.1.1 Public sector R&D

The two main public sector R&D performers are higher education and government research organizations. Government-owned R&D centers are usually involved in missions such as nuclear power, agriculture, construction, health and defense (EC 2003). In recent years, the environment of government-owned laboratory centers has changed considerably. These changes can be seen in the increasing pressure to generate commercial income and technology transfer (Bozeman 1994, OECD 2002) in privatization, or the shift to private management schemes (Boden et al. 2001), the introduction of new business practices and reactions to budget constraints imposed by governments (EC 2003). The indicator measuring this is the level of R&D activity performed in the government sector as a proportion of GDP (GOVERD). To give an overview, Table 2-1 summarizes the R&D activity performed by the government for Finland, Germany and the EU15.

Table 2-1. Public sector R&D (GOVERD).

	Finland	Germany	European Union
1991	0.41	0.35	0.31
2001	0.35	0.34	0.25

Source: OECD (2003); government intramural expenditure on R&D as a proportion of GDP.

Table 2-1 shows that, at the beginning of the 1990s and for a decade after that, Finland and Germany were well above the EU average. Governmental intramural expenditure on R&D relative to GDP has decreased over time in Finland as well as in the EU15. In Germany it has stayed on a constant level.

2.4.1.2 R&D performed by the higher education sector

Universities and other higher education institutes are key elements of the science system in all EU countries. They perform research and train researchers and other skilled personnel. The role of universities and scientific research in the innovation system has broadened in recent years. For example, according to the OECD, there is a "growing demand for economic relevance" in research, and "universities are under pressure to contribute more directly to the innovation systems of their national economies" (OECD 1998). In particular, universities are becoming more dependent on output and performance criteria, and academic research is increasingly mission-oriented and contract-based (EC 2003, OECD 1998). At the same time, universities have established closer links with business through cooperative research, networks and exchange of information (EC 2003). The other basic indicator of public sector R&D covering this is R&D expenditure in the higher education sector (HERD), as depicted in Table 2-2.

Table 2-2. Higher education (HERD).

	Finland	Germany	European Union
1991	0.45	0.41	0.36
2001	0.62	0.41	0.41

Source: OECD (2003); government expenditure on higher education as a percentage of GDP.

In Finland, expenditure on higher education has increased markedly over the decade shown in Table 2-2. In Germany it has stayed at a constant level. Across all countries in the EU15 the share of GDP spent on higher education has increased.

2.4.1.3 Civilian and non-civilian R&D

The benefits of defense R&D spending have been the subject of long-running controversy (Adams 2004). Supporters of defense R&D have traditionally argued that defense R&D has produced important technology spin-offs for the civilian economy. One can distinguish between civilian and non-civilian R&D government outlays for R&D in Table 2-3.

Table 2-3. Civilian and non-civilian R&D.

	Finland	Germany	European Union
Civilian			
1991	98.6	89.0	79.0
2001	98.5	92.6	84.8
Non-Civilian			
1991	1.4	11.0	21.0
2001	1.5	7.4	15.2

Source: OECD (2003); civilian and non-civilian R&D as a percentage of government budget appropriations for R&D. More detailed information comparing the composition of GBAORD in Finland and Germany can be found in Table 3-3 and Table 3-4 below.

2.4.1.4 Tax incentives for R&D

As already alluded to in section 2.3.1 above, tax incentives are typically used to deliver assistance to a broad range of sectors. With tax incentives, each firm has the discretion to decide on which R&D projects to carry out. Tax incentives can be less costly, and less burdensome than direct R&D subsidies.

The fiscal incentives for R&D can take various forms. Some EU countries provide R&D tax credits. These are deducted from the corporate income tax and are applicable either to the level of R&D expenditures or to the increase in these expenditures with respect to a given base. In addition, some countries allow for the accelerated depreciation of investment in machinery, equipment, and buildings devoted to R&D activities. The generosity of R&D tax incentives can be measured by the B index (Warda 1996, 2002). This is a composite index computed as the present value of pre-tax income necessary to cover the initial cost of an R&D investment and to pay corporate income tax, so that it becomes profitable to perform research activities. Algebraically, the B index is equal to the after-tax cost of a one euro expenditure on R&D, divided by one less the corporate income tax rate. The after-tax cost is the net cost of investing in R&D, taking account of all the available tax incentives (corporate income tax rates, R&D tax credits and allowances, depreciation rates).

As neither Finland nor Germany have fiscal incentives for R&D, we present a tax incentive from Denmark in Table 2-4, which also illustrates how to implement an incentive for R&D collaboration within a tax incentive scheme.

Table 2-4. Tax incentive in Denmark.

Title of measure	150% tax deduction on certain research expenditures
Aim	The primary aim is to increase private incentive to cooperate with public research institutions.
Incentives	Persons, companies and funds can receive an additional 50% deduction on certain research projects co-financed by enterprises and public research institutions, the expenditure of which is already 100 per cent deductible.
Requirements	(i) The research project is co-financed by one or more companies and one or more public research institutions. (ii) The company pays between 0.5 and 5 million to the public research institution. (iii) The public institution contributes with own means (iv) SMEs are allowed to deduct their wage costs paid in these projects.

Note: Example taken from TrendChart Innovation (http://trendchart.cordis.lu/tc_datasheet.cfm?id=8480).

2.4.1.5 R&D and innovation subsidies

Government-funded R&D performed by business firms primarily consists of contracts and non-repayable (matched) grants. Other forms of support are guarantees for bank loans, conditional loans and training grants. Government programs allocating direct subsidies are based on specific selection criteria. Firms applying for R&D projects must satisfy some predefined criteria in order to be funded. The indicators in Table 2-5 show government-funded BERD as a percentage of total BERD.

Table 2-5. Percentage of BERD financed by government.

	Finland	Germany	European Union
1991	5.5	10.0	13.5
2001	3.4	6.8	8.0

Source: OECD (2003); percentage of BERD financed by government.

From the early 1990s to the early 2000s we observe a marked decline in the share of industrial expenditure on R&D financed by the government in the EU, Finland and Germany. A discussion of the reasons and consequences of this decline is beyond the scope of the exposition here. Suffice it to point out that the declining share of industrial R&D financed from governmental sources makes an analysis of the leverage governmental funding has on industry's R&D activities even more relevant.

2.4.2 Impact measures of governmental intervention

Having discussed the indicators for the level and pervasiveness of governmental intervention in innovation activities, the next step is to consider what indicators could possibly be used to detect the effect and impact of governmental intervention.

Generally, governmental intervention targets innovation activities. The indicators for detecting the impact of such intervention are the indicators for innovation activities. These indicators can refer to inputs into innovation activities, the outputs and outcome of innovation activity and the conduct of innovation activity. The additional effect of public intervention based on these dimensions is: input additionality, output additionality and behavioral additionality. In some instances we will refer to the Oslo Manual (OECD 1997), since the empirical analysis will utilize data from the Community Innovation Survey which is based on the Oslo Manual.

2.4.2.1 Innovation input

Innovation input indicators measure the effort of companies in innovation related activities. Private R&D expenditure assumes a rather narrow R&D concept of activities related to innovation, whereas innovation expenditure opens the narrow concept towards a broader set of activities.

2.4.2.1.1 Private sector R&D expenditure

R&D expenditure is an indication of the R&D activity in an economy. It shows the amount of resources spent on increasing the knowledge base. This by no means indicates the success of R&D projects. However, it is generally safe to assume that higher expenditure yields increasing knowledge – if not in absolute terms, at least in terms of the probability of creating new knowledge. As discussed above in section 2.1, not all gains from research can be appropriated by the research company. Hence, the overall research activity in an economy will be inefficiently low without public intervention. Governments therefore try to stimulate R&D activity in the economy through tax incentives and research grants.

The complexity of R&D activity and its fuzzy boundaries make it difficult to develop a definition for R&D expenditure. The Frascati manual (OECD 1993) gives a formal definition of R&D activity that was agreed upon by several countries:

> "Research and experimental development (R&D) comprises creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications." (OECD 2003, p. 29.)

In addition, it is stated:

> "The basic criterion for distinguishing R&D from related activities is the presence in R&D of an appreciable element of novelty and the resolution of scientific and/or technological uncertainty, i.e. when the solution to a problem is not readily apparent to someone familiar with the basic stock of commonly used knowledge and techniques in the area concerned." (OECD 2003, p. 33.)

The manual breaks down R&D into basic research, applied research and experimental development. R&D expenditure gives a direct picture of the magnitude of R&D activity on the company or country level. It is therefore widely used in empirical analysis. However, the definition of R&D expenditure is rather narrow. It only focuses on the generation of knowledge. It does not recognize that R&D efforts are carried out for their eventual economic effect, and that these economic effects are yielded only if the results of the knowledge creation can be commercialized successfully.

2.4.2.1.2 Private sector innovation expenditure

Successful product, process or service improvements and novelties require more activities than are captured by R&D expenditure. For instance, the Oslo manual (OECD 1997) defines the term innovation and related activities as follows:

> "Technological product and process (TPP) innovations comprise implemented technologically new products and processes and significant technological improvements in products and processes. A TPP innovation has been implemented if it has been introduced on the market (product innovation) or used within a production process (process innovation). *TPP innovations involve a series of scientific, technological, organizational, financial and commercial activities.*" (OECD 1997, p. 47, emphasis added.)

Market failure not only affects R&D activities, but also influences a broader set of innovation activities. Governmental intervention thus seeks to increase the level of all innovation-related activities which otherwise might be subject to underprovision. The impact of governmental intervention can hence only be measured appropriately by utilizing a concept of innovation expenditure which captures all those activities.

Innovation expenditure encompasses R&D expenditure and includes additional components. It also includes the purchase of patents and licenses, prototyping and tooling-up, training of personnel, the acquisition of embodied technology, industrial design and market research.

2.4.2.2 Innovation output

Innovation output indicators describe the innovation performance of a company. Patent counts, new products, new processes and measures of increased productivity serve as the most prominent measures in this domain.

2.4.2.2.1 Patents

The number of patent applications is an indication of the success of the innovative activity of a firm. Patents relate directly to technologically new knowledge. As such, they are an indication of the increase in the knowledge stock of an economy. Additional knowledge is an important contributor to economic growth. As governments are interested in bringing knowledge generation to a socially optimal level, patents are a useful indicator by which to judge the success of these endeavors. The short time-lag between R&D activity and patent application adds to its attractiveness as an indicator for policy evaluations. National patent offices and the European patent office publish data on the number of patent applications that they receive. Because the data include the name of the applicant, it is possible to relate the patent applications to specific companies for more detailed and firm-level analysis.

However, the propensity to patent differs by firm size, industry, and product complexity. Patents are also to a large extent used for strategic purposes that go beyond protection against appropriability by others. Therefore, a firm may patent useless inventions merely to signal their presence to competitors, discourage new entrants or enter into cross-licensing agreements. Some firms prefer not to patent, but to keep their inventions secret and exploit the time lead on competitors to reap profits from their inventions.

An important advantage of this indicator for empirical research is its widespread availability in all developed countries. Furthermore, since this measure is a by-product of an administrative process, it is of high accuracy. Because of these advantages:

> “...raw patent counts are generally accepted as one of the most appropriate indicators that enable researchers to compare the inventive or innovative performance of companies...” (Hagedoorn and Cloodt 2003, p. 1368.)

2.4.2.2.2 Product innovations

Product innovations comprise technologically new products and significant technological improvements in products. For instance, cellular telephones with internet access are considered as new products, but not cellular telephones that differ from old ones only by the shape or the color of their shell. An improved product is a product with enhanced or upgraded performance. A product innovation has been implemented if it has been successfully introduced on the market. Product innovations involve a series of scientific, technological, organizational, financial and commercial activities (OECD 1997), which on the input side are covered by the innovation expenditure.[8]

The Oslo manual (OECD 1997) differentiates product innovations based on their degree of novelty. The degree of novelty is characterized by the institution the product is new for. Product innovations which are new to the firm are distinguished from product innovations which are new to the market.

New to the firm

Product innovations have a minimum requirement to be at least new to the innovating firm. They do not necessarily have to be new to the market. An indicator measuring the innovation output effect of public funding could be whether or not a company has successfully introduced product innovations that are new to the firm. In addition, the fraction of sales generated by new products captures the economic relevance of new products and indicates the economic success of a company’s innovation endeavors. This figure can be considered as a sales-weighted average of the number of new products. New product counts are

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[8] See section 2.4.2.1.2 above.

not usually collected on a systematic basis by the accounting systems of firms. Sales figures of new products are easier to measure. Moreover, a simple count of new products does not account for differences in the value of the new products. Yet, the share of innovative sales does, because a product innovation receives more weight if it is successful in the market.[9]

However, the measurement of product innovation by the share of innovative sales has one major drawback. It may favor smaller, especially startup firms, whose total sales are mainly composed of new products even though the absolute sales figure due to new products is much lower than for some larger firms producing predominantly unchanged products.[10]

New to the market

The feature of product innovations being new to the market can be considered as a condition for products being new to the world. This applies in most instances, especially when the firm operates globally. The above discussion about new products' share of sales applies here as well.

2.4.2.2.3 Process innovations

Innovation output can take the shape of new processes instead of new products. New processes allow existing products to be produced in a cheaper way, or more efficiently in terms of workers' safety or environmental protection. We can measure the degree of process innovation by the induced cost reduction.

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[9] The Community Innovation Survey (CIS) provides the share in total sales due to new or improved products as a measure of innovation output.

[10] For a discussion of various measures of product innovation, see Kleinknecht (1999).

2.4.2.2.4 GDP per capita growth or labor productivity

The growth rate of labor productivity or alternatively the growth rate of GDP per capita measures the rate at which GDP per capita or employee is increasing. At least some part of the increase can be assumed to reflect the impact of both public and private sector R&D. It is obvious that government and university R&D have a direct effect on scientific and basic knowledge. However, modeling and measuring the productivity effects of public sector R&D is a difficult undertaking for a number of reasons. First public research takes a long time to affect production. Furthermore, public sector research may be undertaken for non-economic reasons and public research often produces public goods (Smith 1991). Second, in some cases the productivity effects of public research cannot be measured because the results are not accounted for in GDP (Guellec and van Pottelsberghe 2003). For example health-related research improves the length and quality of life which is not directly taken into account in GDP measures.

Overall, the expected effect of public sector R&D is positive, though it remains unclear whether the impact is similar to private R&D. On the one hand, there are reasons to suppose that public R&D expenditures might be less productive at the margin, if they are misdirected according to political, rent-seeking objectives. On the other hand, there is evidence that public R&D expenditure is more productive, because the higher education sector concentrates more on basic research which tends to generate more externalities (Guellec and van Pottelsberghe 2003).

2.4.2.3 Other impact measures

Some other impact measures for public innovation intervention are available in the Oslo Manual:

(1) *Ongoing/abandoned innovation activities*. The Oslo Manual also suggests that information on innovation activities which have not yet led to innovative output in terms of product or process innovations is an indirect measure of innovation inputs.

(2) *Organizational innovations*, i.e. changes in the way to do business.

(3) *Cost reduction*. If cost reduction leads to lower prices, then consumer surplus increases, whereas producer surplus increases if prices are kept constant. This output of R&D is especially hard to measure, because many additional factors influence cost reductions.

(4) *Patent citations.* The count of patent applications gives equal weight to every innovation. By using patent counts that are weighted by the number of citations that the patent later received, it is possible to give more weight to more significant innovations.

2.5 Literature review on public intervention and its impact

In this section we briefly review the literature on governmental intervention in innovation. First we focus on the literature concerning the impact of R&D and innovation expenditure and then on the literature concerning the impact of public intervention. There we differentiate the empirical studies based on their level of aggregation.

2.5.1 Impact of R&D expenditure

Most previous studies find that domestic business R&D and foreign R&D are important factors in economic growth. However, few studies distinguish between public and business sector R&D expenditure. Bassanini and Scarpetta (2002) report cross-country regressions that suggest a negative return on public sector R&D. Subsequent research showed that the results of this study may be misleading because it failed to account for the time lag between public R&D investments and productivity outcomes.

Guellec and van Pottelsberghe (2001, 2003) explicitly examine the productivity effects of public sector R&D by using panel data across 16 OECD countries. In particular, they analyze the relationship between national TFP levels and three distinct stocks of R&D capital based on: (1) domestic business-performed R&D; (2) foreign business-performed R&D; and (3) public R&D performed in the higher education sector and in the government sector (public laboratories). They find evidence for lagged effects with a three-year time lag for the initial impact of public sector R&D capital. The long-run elasticity of productivity with respect to public sector R&D and business sector R&D capital is on average 0.17 and 0.13 respectively. Thus, the long run impact of R&D seems to be higher when it is performed by the public sector than when it is performed by the private sector. Furthermore, the elasticity is higher for countries with a relatively large share of university-performed research compared to government lab research. This finding can be interpreted as evidence "that much government-performed R&D is aimed at public missions that don't impact directly on productivity (health, environment), whereas universities provide the basic knowledge that is used in later stages by industry to perform technological innovation". The elasticity of public research is also higher where the business R&D intensity is relatively high, indicating that the spillover benefits of public research are complementary with corporate research activities. (See Table 2-6.)

Another strand of the literature investigates what proportion of firms' products could not have been developed without academic research. Beise and Stahl (1999) find that about 5 percent of new product sales could not have been developed without academic research.

Table 2-6. Benefits of public sector research.

Study	Country	Time period	No. of observations	Dependent variable	Effect
Park (1995)	10 OECD countries	1970–1987	10X16	Change in GDP per capita	positive but not significant
SVR (2002)	21 OECD countries	1980–2000	4X21	Change in GDP per capita	positive effect of HERD % GDP, negative effects of GOVERD % GDP
Bassanini and Scarpetta (2002)	21 OECD countries	1980–1998	16x15	Change in GDP per capita	negative effect of public R&D expenditures
Guellec and van Pottelsberghe (2001, 2003)	16 OECD countries	1980–1998	16x15	Change in TFP	positive effect of public sector R&D
Beise and Stahl (1999)	Germany	1998	2300	Innovation output	5% of new product sales could not have developed without academic research

2.5.2 Impact of governmental intervention

Having established support for a positive relationship between R&D expenditure and the performance of an economy, we turn our focus to the question of how public intervention affects private innovation activities. Section 2.5.2.1 discusses analyses on the macro level, while section 2.5.2.2 discusses studies focusing on firm-level analysis.

2.5.2.1 Macroeconomic studies

The macro-economic studies summarized in Table 2-7 typically exploit the time variation in the data. They use private R&D spending at the country or industry level and regress it on public R&D spending at the same level of aggregation. To avoid a spurious relationship between both variables, it is important to check for macroeconomic influences that can affect both private and public R&D (David et al. 2000). The effect of public basic research on private basic research has been analyzed for the US by Robson (1993) and Diamond (1998). Both authors find an effect of complementarity. Complementarity is also found at the country level for panels of OECD countries (Levy 1990, von Tunzelmann and Martin 1998) and at the industry level for Spanish data (Callejon and Garcia-Quevedo 2003).

Table 2-7. Macroeconomic studies.

Study	Country	Time period	No. of observations	Dependent variable	Effect
Levy (1990)	Nine OECD countries	1963–1984	9x21	Private R&D expenditure	Mostly complementarity
Robson (1993)	USA	1955–1988	33	Change in private basic research	Complementarity
Diamond (1998)	USA	1953–1993	41	Private basic research	Complementarity
von Tunzelmann and Martin (1998)	22 OECD countries	1969–1995	22x27	Change in private R&D	Complementarity
Callejon and Garcia-Quevedo (2003)	Spain	1989–1998	240	Private R&D expenditure	Complementarity

Note: The table is based on David et al. (2000) with modifications.

2.5.2.2 Microeconomic studies

A crucial advantage of microeconomic analysis is its ability to identify industry and firm heterogeneity. Industries differ in the technological opportunities and appropriability of returns from innovation. For companies we expect important differences in innovative activities depending on the company size, international orientation and general business strategy. Microeconometric studies typically concentrate on one country and sometimes on a specific industry within a country.

Due to their ability to identify heterogeneity on both the industry and firm level, microeconomic studies are rather demanding in terms of data quality and availability. They require information about company characteristics *and* about public R&D subsidies. Therefore, these studies have mostly been executed for European countries and the U.S., where the most detailed and reliable data are available.

The dependent variable of interest is usually private R&D expenditure and the question of interest is whether public R&D subsidies succeed in raising private R&D expenditure. Some studies also use R&D or innovation intensity as a dependent variable.

When studying the relationship between public subsidies and private R&D expenditures, analyses on Spanish firms find a positive effect of subsidies on private R&D expenditure (Busom 2000, González et al. 2004). These results are also confirmed by analyses of the German grant system (e.g. Licht and Stadler 2003). The effect of R&D subsidies has also been tested for Israeli (Lach 2002) and French companies (Duguet 2003), again with a positive result. Toivanen and Niininen (2000) concentrate on the relationship between credit constraints and the effectiveness of R&D subsidies. Their empirical study of Finnish firms suggests that R&D subsidies are most effective when directed at firms affected by modest credit constraints. For the U.S., the Small Business Innovation Research program has been evaluated (Wallsten 2000) and crowding out has been found.

Summarizing the literature on the relationship between public and private funding of R&D – the input additionality – the majority of studies finds that no complete crowding out takes place. Due to data restrictions, some analyses cannot differentiate between ‘no complete crowding out’ and ‘complementarity’.

But of the studies which can differentiate, many find that public and private R&D expenditure are complementary.

Czarnitzki and Fier (2003) analyze the patenting behavior of German firms. They test whether companies inside R&D collaborations have a higher propensity to patent. Within the group of collaborating firms, the authors differentiate between participants in publicly funded R&D consortia and participants in non-funded consortia. Because companies select themselves into the different groups, there is a problem of endogeneity that the authors address by means of microeconometric matching. Research consortia do seem to increase the productivity of R&D; companies inside consortia have a higher propensity to patent. In addition, publicly funded R&D consortia have a higher propensity to patent than privately financed consortia. The last result could be due to funding rules requiring firms to patent their research findings. For Finnish firm-level data, Ebersberger (2004a) and Ebersberger and Lehtoranta (2005) find that funding for cooperative R&D increases the innovation output in terms of patenting. For a small subset of firms and projects they also find a positive effect of public funding on the labor demand of funded firms in the medium term.

The introduction of a specific, advanced production technology has also been used as an output indicator at the company level (Arvanitis et al. 2002). The paper investigates whether a Swiss government program was successful in stimulating the introduction of this specific technology. Although the adoption of a new production technology is not an R&D activity in the narrow sense, it nevertheless increases the knowledge base inside companies. The authors conclude that the government program has successfully promoted the introduction of the new technology.

As the discussion above suggests, the effects of collaboration for innovation and public funding overlap if public funding also fosters collaborative arrangements. The effect of collaboration is analyzed in Branstetter and Sakabibara (2002). They use the number of patents as an impact indicator. They compare the patenting behavior of Japanese firms that are a member of a research consortium with firm that are not. They find significantly increased patenting activity for members of research consortia. This is an indication for increased research productivity inside consortia. The authors are also interested in what type of research consortia work especially well. When companies inside the consortia work in similar technological fields, then it is easier to realize spill-over effects. However, when companies compete in the same product markets, they may have an incentive not to share their knowledge with consortium partners. Accordingly, Branstetter and Sakabibara find that technological proximity has a positive effect on the number of patents and that product market proximity has a negative effect. Table 2–8 summarizes the microeconometric studies.

Various microeconometric studies also use national innovation survey data generated as a part of the Community Innovation Survey. Some use the variety of innovation-related variables contained in the innovation surveys (Bouwer and Kleinknecht 1999, Klomp and van Leeuven 2002), while others such as Janz et al. (2003) or Mohnen and Therrien (2003) utilize the fact that the Community Innovation Survey offers internationally comparable data which is essential for cross-country comparisons. Table 2-9 summarizes these studies.

Table 2-8. Microeconomic studies.

Study	Country	Time period	No. of observations	Dependent variable	Effect
Ali-Yrkkö (2005)	Finland	1996–2002	441	R&D expenditure	Complementarity
Almus and Czarnitzki (2003)	Germany	1994–1998	925	R&D intensity	No complete crowding out
Arvanitis et al. (2002)	Switzerland	1990–1996	463	Adoption of specific manufacturing technology	Stimulated by government program
Branstetter and Sakakibara (2002)	Japan	1980–1994	40,635	Patenting behavior	Stimulated by research consortia
Busom (2000)	Spain	1988	154	R&D expenditure	No complete crowding out
Czarnitzki (2001)	Germany	1996, 1998	522	R&D intensity	No complete crowding out
Czarnitzki and Fier (2001)	Germany	1994–1998	2,451	Innovation intensity	Complementarity
Czarnitzki and Fier (2002)	Germany	1996, 1998	1,084	Innovation intensity	No complete crowding out
Czarnitzki and Fier (2003)	Germany	1992–2000	4,132	Patenting behavior	Stimulated by cooperation
Czarnitzki and Hussinger (2004)	Germany	1992–2000	3,779	R&D expenditure Patenting	Positive effect on R&D expenditure, positive effects translate into patenting,
Duguet (2003)	France	1985–1997	1,672	R&D expenditure	Complementarity
Ebersberger (2004b), Ebersberger and Lehtoranta (2005)	Finland	1996–2000	1,894	Patenting behavior	Stimulated by public funding
Ebersberger (2004b), Ebersberger and Lehtoranta (2005)	Finland	1996	115	Labor demand	Positive effect 3 years after project ends
González et al. (2004)	Spain	1990–1999	2,214	R&D expenditure	Complementarity
Fier et al. (2004)	Germany	1992–2000	4,784	R&D expenditure	Complementarity
Hussinger (2003)	Germany	1992–2000	3,744	R&D expenditure	Complementarity
Lach (2002)	Israel	1990–1995	134	R&D expenditure	No complete crowding out
Licht and Stadler (2003)	Germany	1992–2000	7,878	R&D expenditure	Complementarity
Toivanen and Niininen (2000)	Finland	1989–1993	133	R&D expenditure	Mixed, substitutability
Wallsten (2000)	USA	1990–1992	479	R&D expenditure	Substitutability

Table 2-9. Microeconomic studies using innovation survey data.

Study	Country	Type of government support	Measure of innovation	Effect on innovation
Brouwer and Kleinknecht (1999)	Netherlands, 1988 SEO National Survey on R&D and Innovation, and CIS 1	Participating in an EC R&D program in 1991 or in 1992	R&D	Positive
Criscuolo and Haskel (2002)	UK, CIS 2	Government financial support, and innovation related govt. programs	Dichotomous data on process innovation or on product innovation	Sometimes significant
Klomp and van Leeuwen (2002)	Netherlands, CIS 2	Innovation subsidies	R&D intensity, share of innovative sales	Positive
Janz et al. (2003)	Germany, Sweden, CIS 3	Financial support for innovation	Innovation expenditures, innovative sales	Mostly insignificant
Mohnen and Therrien (2003)	France, Germany, Ireland, Spain, CIS 2, 1999 Canadian Survey of Innovation	Government support for innovation	Categorical shares of innovative sales	Significant in European countries

2.6 Summary

Since R&D activity is a main driving force for economic growth, it is important to ensure that it occurs at an optimal level. Without governmental intervention we expect an underprovision of R&D and innovation activity. Companies cannot completely exclude competitors from using their results. Because companies realize the appropriation problem, they engage in research less than would be optimal. Governments therefore intervene by investing directly in R&D activities (e.g. expenditures for higher education) and by employing tax breaks and grants as incentive mechanisms to raise private R&D activity.

An analysis of the effects of public intervention is warranted for reasons of accountability and transparency. R&D subsidies should only be used if they indeed increase private R&D spending. This condition is necessary, but not sufficient. In order to justify R&D subsidies, we also demand that the potentially increased R&D activity eventually translates into increased innovation output.

It is then an important task to analyze the effects of governmental intervention. When analyzing the effects of R&D subsidies, the researcher is confronted by several problems. It is necessary to account for the heterogeneity of participating companies, to correct the self-selection of companies into grant programs, and, finally, to consider issues of comparability of data across time.

Concerning public innovation intervention, it has been found that public sector R&D has a positive influence on the total productivity factor measured at the country level. The relationship between public R&D expenditure and private R&D spending has been analyzed at the country and company levels. Most studies find a relationship of complementarity. It has also been found that patenting inside research consortia, especially public-funded consortia, is higher.

Historically, studies to measure the impact of governmental intervention in R&D were focused on the macroeconomic level. There, the advantages were good data availability at the country level and ease of computation due to the limited number of observations. Their disadvantages lie in their inability to identify industry effects or to differentiate between different types of companies. Today, the general tendency favors studies at the microeconomic level. Data availability has improved and the advantages of controlling for heterogeneity at the industry and company levels have been recognized.

By and large, the surveyed literature provides evidence of positive effects of public funding on both innovation input such as R&D expenditure and innovation output in terms of patenting. However, the research on the effect of public intervention on the innovation output is less developed than it is for the impact on innovation input. In addition, the international comparability of the studies is rather underdeveloped. Finally, no internationally comparable analysis has been carried out for the impact of public funding in Finland.

3. General trends of innovation policy in Germany and Finland

In this section, which sketches the general trends of innovation policy in Finland and Germany, we explicitly focus on innovation and R&D policies, the public funding system and various input and output indicators of the national innovation system.[11]

[11] To a large extent this section is based on Czarnitzki et al. (2004b).

3.1 Introduction

The trends of Government expenditure on R&D and innovation are important indicators of where scientific progress is to be advanced with government funding. At any given time, the level of government funds earmarked for R&D and innovation, and their allocation to the various funding areas and priorities, are particularly important. The comparison of Finnish and German innovation policy trends is of particular interest, because, although both countries have similar policies, their degree of success has been different in recent years. A comparison of Finnish and German innovation policy trends is even more relevant for the discussion later in this analysis, as the impact of public funding in Finland will be compared with the impact of public funding in Germany. Finland and Germany belong to both the European Union and the OECD. Within this framework, both countries are subject to a common currency area, commercial agreements and a common European legal framework. Both countries contribute common economic indicators to the OECD for cross-country comparisons. 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

(1) a comparable national innovation and R&D policy

(2) comparable policy instruments aimed at stimulating business R&D

(3) a comparable public funding system.

In the following sections we will briefly sketch these three features of the national system of innovation in both countries. Finally, we will elaborate on some input and output characteristics of their national innovation systems.

3.2 Innovation and R&D policies

In Germany the main objective of innovation policy (in a broader sense) is to accelerate the diffusion of new technologies and to ensure that Germany is able to keep pace with international technological developments. In 2001, the Federal Government's expenditure on research and development amounted to EUR 7,099 million, which represented a 2.8 percent increase on the year 2000 (OECD 2003).

The contributions made by the Federal Ministry of Economics and Technology (BMWi)[12], the Federal Ministry of Defense (BMVg) and the Federal Ministry of Education and Research (BMBF) account for almost 90 percent of the total federal R&D funds. Nearly two-thirds of all federal R&D expenditure is financed by the budget of the BMBF. In recent years, innovation activities have been redesigned towards clearer structures and competition-orientation. Improved structures are achieved by distinguishing three lines of promotion (innovation, cooperation, technological consulting). SMEs are the main targets of innovation promotion. Special emphasis is put on innovation at the interface of science and industry. Therefore, innovation promotion strongly addresses the transfer of technology from science to commercial use, the cooperation between firms and research institutes, and the support of start-ups introducing new technologies and products that are new to the market.

Furthermore, the use of IPR is enforced by several measures. R&D expenditure growth rates for the BMBF have been continuous and far higher than the average. An increase in 1999, when the BMBF's R&D expenditure was up 3.5 percent on the 1998 level, has been followed by a continuing positive trend. Following a further increase in 2000 – by 2.9 percent with respect to 1999 – the upward trend has included increases of 7.6 percent compared with 2000 and 3.5 percent compared with 2001 (cf. Fier 2002, BMBF 2000).

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[12] Since autumn 2002 the BMWi has been part of the Federal Ministry of Economics and Labor.

Table 3-1. Relative gross domestic expenditure on R&D.

Year	Germany					Finland				
	Share of GERD		Share of GDP			Share of GERD		Share of GDP		
	Private	Public	Private	Public	Total	Private	Public	Private	Public	Total
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
1998	62.34	34.86	1.44	0.81	2.31	63.88	30.05	1.84	0.87	2.88
1999	64.96	32.55	1.58	0.79	2.44	66.95	29.18	2.16	0.94	3.23
2000	65.80	31.64	1.58	0.79	2.49	70.25	26.23	2.39	0.89	3.40
2001	65.99	31.53	1.64	0.78	2.49	70.78	25.52	2.41	0.87	3.40

Note: Share given in %. Source: OECD (2003).

In recent years Finland's technology policy has focused on the creation and application of new knowledge and skills, on the integration of well-being and sustainable development and the capacity for continuous renewal. Finland has striven to create a favorable environment for innovation and business activities. Economic and societal development in Finland has been based on developing and diffusing high technology both domestically and internationally. The latter has resulted in increased efforts to foster exports. Finland's exports in 2002 amounted to EUR 47,000 million and its imports to EUR 35,000 million. International trade statistics show that high-tech products account for 20.6 percent of Finland's exports. These efforts have finally resulted in favorable international competitiveness for the Finnish economy. Although Finland exhibited rather mediocre productivity in the late 1980s and early 1990s (Hämäläinen 2004), it has recently ranked as one of the leading European countries for innovation as measured in terms of growth, competitiveness, technological sophistication and infrastructure (Porter et al. 2004, IMD 2004, Schienstock and Hämäläinen 2001). Not all studies of Finnish competitiveness and technological success paint an equally positive picture, especially if societal and environmental aspects are taken into account (cf. e.g. Naumanen 2004). EU science and technology indicators depict Finland, Sweden and Denmark as countries that are rapidly transforming into knowledge-based economies.

In Finland, the Science and Technology Policy Council, chaired by the Prime Minister, plays a key role in co-ordinating innovation policy activities at the national level. The Council membership consists of the Minister of Education, the Minister of Trade and Industry, the Minister of Finance, four other ministers, and ten other members well versed in science or technology (representatives of the Academy of Finland, the National Technology Agency, and industry and employers' and employees' organizations). The main tasks of the Council include directing science and technology policy, dealing with the overall development of scientific research and education, and issuing statements on the allocation of public science and technology funds to the various ministries and interested bodies.

Like the German structure of ministries, the two most important ministries in the Finnish national innovation system are the Ministry of Education and the Ministry of Trade and Industry. In 2003 the former administered 41.7 percent and the latter 34.4 percent of the governmental outlays on R&D (Statistics Finland 2004). Occupying the center of the administrative field of the Ministry of Education are the universities and the Academy of Finland.

The Ministry of Trade and Industry is responsible for technology policy and for providing support for industrial research and development. It also exercises prime responsibility for issues related to EU research in Finland. The administrative field of the Ministry of Trade and Industry contains a number of business support organizations influencing the innovation activities of Finnish firms (Georghiou et al. 2003). Within the administrative field of the Ministry of Trade and Industry the National Technology Agency (Tekes) plays an exceptional role in planning and financing technical research and development.

In general, the Finnish catching-up process has been heavily determined by its fundamental structural shift from a resource-based economy to a knowledge-based economy. R&D has been a key factor in this development. However, 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 and in the early 2000s Finland was among the largest R&D spenders (relative to GDP) of all OECD counties (OECD 2003). Table 3-2 shows the gross domestic expenditure on R&D as a percentage of GDP in the context of other OECD countries.

During the same period Germany has had to cope with the consequences of its reunification in 1989 and the transformation of East Germany. Budgets in all areas of German life have been severely strained by the massive efforts required by the reunification process.

Table 3-2. GERD as percentage of GDP for OECD countries (2001).

Country	2001	Country	2001	Country	2001
Australia	1.55[1]	Hungary	0.95	Poland	0.67
Austria	1.92	Iceland	3.08	Portugal	0.84
Belgium	2.17	Ireland	1.17	Slovak Republic	0.65
Canada	1.91	Italy	1.07[1]	Spain	0.96
Czech Republic	1.30	Japan	3.06	Sweden	4.27
Denmark	2.39	Korea	2.92	Switzerland	2.63[1]
Finland	3.42	Luxembourg	1.71[1]	Turkey	0.64[1]
France	2.23	Netherlands	1.89	United Kingdom	1.89
Germany	2.51	New Zealand	1.18	United States	2.74
Greece	0.64	Norway	1.60		
Total OECD	2.29				
European Union	1.93				

Source: OECD (2003), 1 data referring to 2000.

3.3 Policy instruments fostering business R&D

Innovation policies rest on several pillars: direct subsidies for research projects within thematic programs, promotion of SMEs in three promotion lines (innovation, cooperation, technology consulting) and by four types of support (subsidies, loans, venture capital, and infrastructure supply) in the fields of information and consulting. In general, firms can compose from the different pillars an individual mix of public support that best suits the firm's specific challenges. In contrast to other EU Member States, neither Finland nor Germany have fiscal incentives for R&D.

Using the “Trend Chart on Innovation in Europe”[13] as a practical tool for innovation organization and schemes in Europe, three different categories of policy objectives and instruments can be identified (cf. Rammer 2003, Kutinlahti and Oksanen 2003):

(1) Fostering an innovation culture:

 (a) promoting the benefits of innovation which includes measures stimulating creativity, initiative and enterprise, calculated risk-taking, acceptance of social, geographical and professional mobility

 (b) developing skills including those dealing with information collection and processing and personal and social communication skills

 (c) developing the ability to anticipate needs and improve organizational capabilities; improving awareness dissemination and strengthening cooperation in order to transfer skills and experience.

(2) Establishing a framework conducive to innovation:

 (a) permitting innovation to flourish and grow; allowing cooperation to operate correctly

 (b) the effective and economical protection of intellectual property

 (c) reducing the burdens to on enterprises, while maintaining consumer safeguards

 (d) allowing access to funding; easing the financial constraints on innovation.

(3) Gearing research towards innovation:

 (a) improving the way in which the fruits of research are transformed into products, processes, services and, hence, contribute to competitive advantage and the societal good

[13] http://trendchart.cordis.lu/

(b) includes strategic planning of innovation policies, support for the RTD process, identification of spin-offs, creation of new innovating firms, and stimulation of cooperation between the public, private and education sectors.

With respect to these innovation policy objectives and schemes in favor of science and the business enterprise sector, direct subsidies are the most important innovation policy tool in both Finland and Germany. Direct subsidies belong to the group of policy instruments that focus on innovation financing, i.e. the provision of finance for innovation activities, including measures designed to deliver or stimulate delivery, or financial support for innovation, including:

(1) mobilization of private capital, equity finance, venture and risk capital

(2) the promotion of investment in R&D

(3) the creation of guarantee mechanisms

(4) the operation of stock markets, especially for growth enterprises

(5) the dissemination of information

(6) the development of specialist training

(7) the provision of advice

(8) schemes to disseminate best practice and experience.

With regard to the promotion of investment in R&D, two important policy trends must be stressed. First, direct R&D and innovation subsidies are given as *matched grants*.[14] Second, direct R&D and innovation subsidies are preferably given for collaborative research projects.

(1) *Matching grants* for R&D projects are directed at thematic programs, adoptions of program structures based on technology foresight,

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

regular tenders and peer review-based selections, and special approaches (e.g. joint projects of 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 management organizations (*Projektträger*).

(2) *Collaborative research* is preferred in R&D projects because cooperation has advantages such as positive spillovers and cost and risk sharing. In an empirical study, Cassiman and Veugelers (2002) and Dachs et al. (2004) explore the effects of knowledge flows on R&D cooperation. Their results suggest that firms with higher incoming spillovers and better appropriation have a higher probability of cooperating in R&D.

Networking and close university-industry cooperation are seen as key strengths in both Finland and Germany. About 50 percent of the innovating companies in *Finland* have been involved in cooperative research and development. Judging by the frequency of use in 1998–2000, suppliers (41 percent), customers and clients (38.1 percent) and universities (29.1 percent) are the most important partners for collaborative research (Statistics Finland 2002). Even though they are among the least important collaboration partners, competitors and research labs are collaborated with by about one fifth of innovating firms. According to OECD data, Finland has the second largest (after Sweden) share of firms with cooperation agreements with universities or government research institutes.

In *Germany* we find that 16.5 percent (1998–2000) of firms have a cooperation agreement. This means 15.1 percent of SMEs and 46.4 percent of firms with over 500 employees. 15.3 percent of German firms cooperate with partners in Germany, while 6.7 percent have foreign cooperation partners. 10.2 percent of German firms cooperate with universities (1998–2000). It is evident that the percentage of firms with a cooperation partner in every documented class of partner has somewhat declined since the mid-1990s. The only exception is the percentage of firms that cooperate with commercial laboratories and R&D

enterprises: This percentage rose to 4.4 percent.[15] Network support strives to close the gaps in the value chain and overcome structural weaknesses in the innovation system. Moreover, they aim at sharpening the regional profile with marketing, reputation management, and public consultancy. The German *networks of competence* also aim at providing core tasks of cluster management and offering an institutionalized model for developing cluster awareness.

The comparison of the German and Finnish collaboration pattern reveals a strikingly higher propensity to collaborate in Finland. This observation relates not only to the years 1998 to 2000 reported here, but also to the mid-1990s where we find comparable results (Foyn 2000). The reasons for this difference in the propensity to collaborate can be explained by two main observations. First, the small size of the Finnish economy facilitates networking due to the comparatively 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 Finland and Austria (cf. Dachs et al. 2004, Foyn 2000), size cannot be the whole story. Secondly, and more importantly, we observe that the strengthening of inter-firm networking and cooperation 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 developed in Finland, as it has a longer history of a collaboration-targeted public funding policy than most other European countries (Schienstock and Hämäläinen 2001). Since the National Technology Agency (Tekes) started its first technology program in the early 1980s, collaboration has been a part of the financing principles (cf. e.g. Lemola 2002). However, Tekes' notion of collaboration is not focused on a special kind of collaboration, but includes a whole plethora of different types of networks covering the whole spectrum of activities from basic R&D up to commercialization and marketing. It induces pre-competitive horizontal collaboration, vertical cooperation and networks of small and medium sized companies with R&D institutions or large companies. The latter can hardly get funding unless they cooperate with SMEs or R&D institutes.

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[15] The numbers presented in this paragraph are based on the CIS survey and are provided by the ZEW, Mannheim, Germany.

3.4 Public funding system

Within the administration of German and Finnish ministries, particular organizations (intermediaries) are responsible for the process of funding R&D and innovation. These intermediaries have a central position in planning and financing. In Germany the administration of public funds is mainly delegated to and carried out by project management organizations (*Projektträger*), whereas in Finland these tasks belong to the National Technology Agency (Tekes).

The German project management organizations are in charge of the technical and organizational realization of ministerial projects. Qualified experts in different scientific and technical areas and competent contact persons perform the following functions through all project stages:

(1) conceptual work in preparing new support programs and emphases

(2) project management (advisory services for applicants, professional and administrative phase-out of current projects, evaluation)

(3) supervision of EU support programs

(4) support in international research cooperation

(5) public relations.

For this reason the German project management organizations are the most important contact points in the promotion of research. To cope with the responsibility of the funds entrusted to them, they must ensure that projects are carried out with a high degree of professionalism and that the legal framework of the promotion of the project is considered. The project management organizations are service enterprises and administrate up to EUR 500 million per year in subsidies. Actually, the German Federal Ministry of Education and Research (BMBF) has eleven project management organizations.

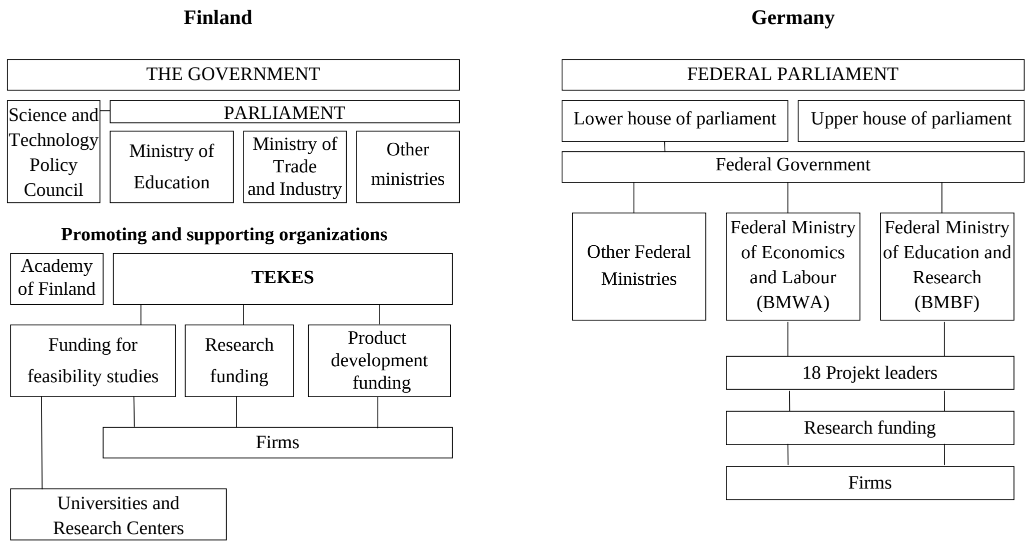

Figure 3-1. R&D funding systems in Finland and Germany.

In the *Finnish* innovation system, Tekes (the National Technology Agency) is the counterpart to the German project management organizations. It focuses on supporting firms and scientific institutes. Tekes is the main source of public funding for applied technological research and industrial R&D. It seeks to promote the competitiveness of Finnish industry and the service sector by promoting research and applications in the field of technological development.

Tekes prepares funds and coordinates national technology programs, and provides funds for applied technical research. Being administered by the Ministry of Trade and Industry, it also contributes to the preparation of national technology policy. Controlling 27.1 percent of government R&D appropriations (EUR 392 million in 2003), Tekes is the largest organization in the field (Tekes 2004a). In 2003, Tekes supported R&D efforts through industrial R&D grants (39.8 percent), research funding for universities and research institutes (41.3 percent), industrial R&D loans (10.2 percent) and capital loans for R&D to companies (8.7 percent). The type of funding for companies depends on the stage of the innovation and the nature of the project.

In Germany and Finland industrial R&D grants run from about 15 percent to 50 percent of the eligible costs. Capital R&D loans run from 35 percent to 60 percent and industrial R&D loans from 45 percent to 70 percent of the eligible costs (Finland). The funding share for research institutes and universities ranges from 50 percent to 100 percent of the eligible costs and is restricted to research work done at the institute or university. These projects are usually cooperative arrangements with companies or other research facilities. Technology programs are initiated by Tekes or the German project management organizations, and concentrate on specific technological fields. The programs run for a duration of three to five years on average. The funding organizations usually finance about half of the program costs.

3.5 Input and output indicators on R&D and innovation

The Finnish government spent about EUR 1,400 million on R&D activities in 2002. Although this is less than one tenth of the German government support of about EUR 17,000 million, the different size of the economies has to be taken into account: In 2001 Finland spent 3.4 percent of its GDP on R&D, whereas Germany spent 2.5 percent. Moreover, the public R&D intensity in Finland is 0.96 percent, which exceeds that in Germany by 0.16 percent (OECD 2003).

In the late 1990s, the Finnish governmental outlays for R&D were markedly increased by a government decision to allocate EUR 500 million to research and development over the years 1997 to 1999. This additional appropriation for R&D was financed by privatization revenues. In 1999, the additional increment (EUR 250 million) was introduced permanently. The objective was to foster the national system of innovation to create a beneficial environment for business, employment and the economy. In numbers, the final aim was to raise R&D to 2.9 percent of GDP by 1999. This goal had already been achieved by 1998.

Considering Finnish innovation activities in the years 1995 to 2001, it turns out that Finnish R&D expenditure increased by a higher rate (90 percent) than that in Germany (23 percent). Aggregate R&D expenditure in Finland is shaped by the private ICT sector (Nokia effect). The growing importance of the electronics industry from the early to the late 1990s is reflected in an increase in its share of private R&D expenditure from about 25 percent in 1990 to about 54 percent in

1999 (Statistics Finland 2001). OECD cross-country analysis uses coherent indicators that are the most suitable in measuring the stimulation and performance of public and private R&D investments. As discussed above, indicators such as GERD (Gross domestic expenditure on R&D), GBAORD (Government Budget Appropriations or Outlays for R&D by socio-economic objectives) or R&D Personnel (FTE) show the distribution and share of R&D investments of a national economy. Comparable data for Finland and Germany are contained in Table 3-3 and Table 3-4.

Table 3-3. R&D input and output indicators for the Finnish IS.

Finland	1991	1993	1995	1997	1999	2001
GBAORD (million current PPP $)	755	861	944	1,204	1,280	1,368
GBAORD in % of GDP	0.95	1.06	0.98	1.11	1.06	1
GERD in % GDP	2.03	2.16	2.28	2.71	3.23	3.4
Public share of GERD in %	40.9	39.83	35.09	30.86	29.18	25.52
Private share of GERD in %	56.32	56.62	59.47	62.9	66.95	70.78
Total researchers (FTE)	14,030	15,229	16,863	26,483	32,676	36,889
Decomposition GBAORD in %:						
Defense Budget R&D as % of total GBAORD	1.43	2.11	2.08	1.54	1.37	1.55
Civil Budget R&D as % of total GBAORD	98.57	97.89	97.92	98.46	98.63	98.45
Economic Development programs as % of civil GBAORD	41.01	46.58	46.80	41.31	42.87	41.42
Health and Environment programs as % of civil GBAORD	16.53	15.10	13.91	17.00	16.22	15.66
Space programs as % of civil GBAORD	3.10	3.07	2.25	2.55	2.59	2.19
Non-oriented research programs as % of civil GBAORD	10.65	10.52	10.16	12.28	12.62	14.43
General University Funds (GUF) as a % of civil GBAORD	28.70	24.73	26.89	26.85	25.7	26.3

Source: OEDC (2003).

(1) *GERD:* Splitting the GERD into public and private shares reveals that the ratio of public and private R&D in Germany is constant at about 1:2 in the considered period. In Finland, the relative importance of public R&D declined from 1990 to 2003. Public R&D expenditure could not keep pace with the fast-increasing private R&D expenditure fuelled by the successful electronics industry.

(2) *GBOARD:* Although the Finnish GBOARD is much lower than the German GBOARD, the growth rate in Finland is significantly higher than in Germany. According to the OECD indices, the Finnish GBOARD rose by about 113 percent from 1990 to 2003, whereas the German GBOARD rose by just 50 percent from 1990 to 2002. Relative to GDP, the GBOARD and GERD in Finland exceeded the German figure by a small amount. With respect to the composition of the GBOARD in Germany in 1990–2003, the share of the defense budget declined continuously, while general university funding grew.

(3) *FTE:* The pattern of the growth rates reveals huge progress in Finland. From 1995 to 2001, the number of Finnish researchers grew by more than 30 percent, whereas the number of German researchers grew by 17 percent in the same period.[16]

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[16] The number of researchers in the summary table gives a quantitatively different picture, as some breaks in the Finnish data series have to be accounted for. The qualitative findings are left untouched, however. The numbers in the text are based on the OECD's computation on the compound growth rate of the number of researchers.

Table 3-4. R&D input and output indicators for the German IS.

Germany	1991	1993	1995	1997	1999	2001
GBAORD (million current PPP $)	14062.1	14,923	15,697	16,118	16,696	17,766
GBAORD in % of GDP	1.00	0.97	0.90	0.86	0.82	0.82
GERD in % GDP	2.53	2.35	2.26	2.29	2.44	2.49
Public share of GERD in %	35.68	36.12	36.80	35.90	32.55	31.53
Private share of GERD in %	61.86	61.91	61.13	61.36	64.96	65.99
Total researchers (FTE)	241,869		231,128	235,793	254,691	259,597
Decomposition GBAORD in %:						
Defense Budget R&D as % of total GBAORD	10.98	8.52	9.06	9.57	8.33	7.15
Civil Budget R&D as % of total GBAORD	89.02	91.48	90.94	90.43	91.67	92.85
Economic Development programs as % of civil GBAORD	25.53	22.81	22.98	22.85	22.61	21.07
Health and Environment programs as % of civil GBAORD	13.03	13.36	12.63	12.53	13.02	14.45
Space programs as % of civil GBAORD	6.05	6.37	5.66	5.27	4.92	5.04
Non-oriented research programs as % of civil GBAORD	17.04	16.74	16.52	17.11	17.41	17.38
General University Funds (GUF) as a % of civil GBAORD	37.26	40.53	41.49	42.56	41.79	42.00

Source: OEDC (2003).

The remarkable catch-up process that took place in Finland in the 1990s is shown not only by the input indicators, but also by selected innovation outcome and output indicators such as patents. It has been argued that the success of the Finnish innovation system can be partly attributed to the fact that it has been able to supply an ever increasing number of science and engineering graduates (c.f. Georghiou et al. 2003).

Table 3-5. Number of patent applications.

	Development of the number of patent applications to the EPO (priority year), 1990=100			Development of the number of patent applications to the USPTO (priority year), 1990=100		
	Finland	Germany	European Union	Finland	Germany	European Union
1990	100.0	100.0	100.0	100.0	100.0	100.0
1991	96.7	98.9	99.7	101.2	106.4	99.6
1992	121.5	100.3	100.1	102.5	125.6	98.8
1993	135.4	102.6	103.2	108.8	142.4	102.4
1994	159.4	109.0	109.2	117.2	164.3	109.3
1995	162.5	113.7	114.5	127.0	166.0	115.9
1996	192.8	135.8	132.7	145.3	194.3	122.0
1997	233.4	152.2	149.2	155.5	205.7	133.0
1998	263.9	169.9	163.3	161.3	216.0	132.9
1999	322.0	182.2	177.6	156.1	214.4	126.0
2000	310.1	189.6	183.3			

Source: OECD (2003).

The number of patents is an output variable that is seen as an important yardstick of a nation’s future technological competitiveness. The objective of both German and Finnish research is not only to contribute to scientific knowledge, but to make the most effective and efficient commercial use of research results. In international statistics, innovative capacity is often measured by patents.[17] 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 planning further R&D activities. Moreover, patent indicators are an important measure by which governments can classify their country’s innovativeness in the international technology competition. (See Table 3-5.)

[17] Cf. OECD (1994) for a comprehensive discussion on the use of patents as science and technology indicators.

The German Federal Government stimulates patenting, licensing and exploitation expertise in their funding procedures. When an R&D recipient files an application, the firm already has to submit a plan for utilization – initially in the form of an outline that will subsequently 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 grant recipients, the Federal Government allows them to keep all proceeds from the exploitation of their patents for at least two years. If the recipient does not apply for a patent within two years, the R&D results become a public good (BMBF 2000). In contrast to the German practice, funded companies in Finland do not have an additional incentive beyond the usual IPR to patent the results of the funded research that is built into the funding scheme.

3.6 Summary

This section showed that Finland and Germany have a comparable national innovation and R&D policy, a comparable set of policy instruments aimed at stimulating business R&D and a comparable public funding system. Despite these commonalties, they experienced different success in terms of technological and economic development. The analysis that follows does not aim to explain the differential performance of the Finnish and the German innovation systems. Rather it argues that, despite the different performance, the Finnish and German funding schemes and their effects can be compared.

4. Data and methodology

________ *This section introduces the Community Innovation Survey and the data used for the empirical research presented in the following sections. It also investigates, in a cursory manner, the microeconometric methodologies which could potentially be used for empirical investigation into the impact of public R&D subsidies. It also singles out the useful methodologies for the investigation.* ____________________________

4.1 Introduction

After having stressed the need for internationally comparable results in the previous section we focus our attention on the data and empirical methodologies that are available to assess the impact of public intervention in the form of public subsidies. We introduce the Community Innovation Survey as the data set that allows us to conduct an analysis which is comparable for both Finland and Germany. Then we turn to methodological issues and discuss the empirical approaches that will be employed in the course of this study. The methodological approach is challenged by the fact that – as in any research context in social sciences and economics – the data are not experimental. Thus, for the evaluation tasks of this analysis, the same firm cannot be observed twice under alternative funding conditions.

4.2 Data

The data basis for this analysis 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 by surveying innovation activities at the enterprise level in the Member States' economies. The CIS surveys collect firm-level data on innovations across member states by means of largely harmonized questionnaires. Thus the data are comparable on the European scale and are based on a representative sample of companies within these economies. In this analysis we use the second and third waves of the Community Innovation Survey (CIS II and CIS III) in which CIS II covers the years 1994 to 1996 and CIS III covers the years 1998 to 2000.

As mentioned above, the Community Innovation Survey closely reflects the definitions of the Oslo Manual (OECD 1997) and thus provides a good coverage of the indicators that could potentially be used to detect the effect of government intervention in innovation. Table 4-1 and Table 4-2 summarize the availability of the measures in the Community Innovation Survey. Appendix A contains a copy of the CIS III questionnaire.

Table 4-1. Indicators to measure government intervention.

Indicators	Available in CIS
Size of tax reduction	–
Tax reduction (dummy)	–
Size of public funding, size of grants	–
Public funding (dummy)	X

Note: The availability of indicators here only refers to the Finnish and German CIS II and CIS III.

Table 4-2. Indicators to measure the effect of govt. intervention.

Indicators	Availability in CIS
Input	
Nominal R&D effort (R&D expenditure)	X
Real R&D effort (R&D personnel)	X
Innovation expenditure	X
Ongoing/abandoned innovation projects	X
Output	
Patenting activity	X
Patent counts	X
Patent counts weighted by citations	-
Product innovation	X
Product innovation new to the firm	X
Product innovation new to the market	X
Share of sales by new products (to the firm)	X
Share of sales by new products (to the market)	X
Process innovation	X
Cost reduction	–
Organizational innovations	X
Behavior	
Collaboration for innovation	X

Note: The availability of indicators here only refers to the Finnish and German CIS II and CIS III.

Although Table 4-2 reveals an abundance of indicators to measure the effect of governmental intervention, we restrict the analysis below to two essential categories covering the input and output dimensions. We analyze the effect of governmental intervention on innovation expenditure and patenting activity. Table 4-1 indicates the available measures of governmental intervention available through the Community Innovation Survey. Apart from the measures of effects, the Community Innovation Survey contains quite limited information on the type and extent of governmental intervention. Essentially, we can only utilize the dummy variable on whether individual firms received public funding for their innovation activities from national or regional sources. The CIS data does not contain information on the size of the grants received. Besides containing data on information-related innovation activities, the Community Innovation Survey has data on firm characteristics such as size, sector, investment and exports.

The analysis below will not only draw upon the Community Innovation Survey, but also utilize data on the patenting history of individual firms through their patent applications at national patenting offices.[18] Given the data available, governmental intervention in innovation can only be captured by the dummy variable indicating the receipt of public funding. However, we will also be able to assess the impact of collaboration on innovation as a behavioral characteristic of the firm.

Each empirical analysis below will discuss the used data source in detail, as we supplement the data with data from other sources where necessary.

4.3 Impact assessment with non-experimental data

The impact assessment methodologies revolve around the evaluation problem that occurs if – as is common in social science and economics – no experiments can be conducted. Briefly, the evaluation problem exists because, at any given

[18] For the Finnish part of the analysis the patenting data and CIS data were kindly supplied by Statistics Finland.

point in time, a firm can be either treated or not treated.[19] A firm cannot be treated and not treated at the same time. Hence the difference in behavior or performance – which we denote as impact – cannot be observed directly. For the treated companies we can only observe their behavior and performance for the state of treatment. To assess the impact of treatment we would have to know what the company would have done and how it would have performed in the case of not being treated. This is not observable. This missing data problem lies at the core of the evaluation problem.

Generally, there are six types of approaches that can be pursued to overcome the missing data problem and assess the impact of a treatment (Blundell and Costa Dias 2000):[20]

(1) *Pure random experiments.* In pure random experiments a random sample of the firms eligible for the treatment are selected and not treated and represent the control group. Their behavior and performance is used to construct the counterfactual. Although being preferred from an evaluation point of view (e.g. Jaffe 2002) they have certain disadvantages. Random experiments are expensive to implement as, for the sake of assessing the input, they are required to sacrifice a considerable fraction of the potential impact. They cannot be extrapolated and hence the results are not applicable to ex ante assessment of comparable treatment programs. Finally and most importantly for the evaluation pursued here, pure random experiments have to be integrated in the program design right from the start, as they require a special randomized selection of firms out of the eligible applicants. As pure random experiments are not implemented in public R&D funding – neither in Finland nor in Germany – we cannot follow this approach in our impact assessment exercise.

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[19] In the discussion of the methodological approach to assess the impact of governmental intervention we will use the term treatment as a generalization for public funding, or collaboration for innovation, or both.

[20] As we want to give a quite general introduction to the measurement of the impact of R&D funding and R&D collaboration later on, we use the abstractum treatment to indicated either R&D funding or R&D collaboration or both. In the empirical discussion below, we are more explicit on the type of treatment we refer to.

(2) *Structural simulation modeling.* Structural simulation modeling has been used to assess the impact of programs where robust behavioral models are available to depict the behavior of the treated firms. Blundell and Costa Dias (2000) point out that the advantage of the structural simulation models is their ability to simulate the outcomes of programs in which individuals' preferences – and firms' technologies – do not change, but their constraints change. Given its strong dependence on robust behavioral models, structural simulation modeling cannot be applied in our context, as no robust behavioral models exist on how R&D inputs translate into R&D outputs and outcome. Moreover, as R&D is particularly targeted at changing companies' technologies, we cannot maintain the assumption that firms' technologies will not change.

The remaining four approaches all relate to situations where non-experimental data are available. The selection among those is influenced by data availability, the underlying model and the research question:

(3) instrumental variable estimation

(4) diffs-in-diffs approach

(5) selection models

(6) matching.

Instrumental variable estimation and the Heckman selection models can be used when the data at hand consist of only one cross-section. If panel data or repeated cross-sections are available, the diffs-in-diffs approach can be used. The matching approach, which will be the core of the analysis tool kit used in the empirical analysis below, can be used if either cross-section or panel data are available.

Before we turn to a discussion of the above-mentioned impact assessment methodologies for non-experimental data in more detail in section 4.3.2 to section 4.3.5, we will discuss the difference between homogenous and heterogeneous treatment effects in section 4.3.1.[21]

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[21] The discussion in section 4.3 will broadly follow Blundell and Costa-Dias (2000).

4.3.1 Homogeneous and heterogeneous treatment effects

The distinction between homogeneous and heterogeneous treatment effects relates to the basic assumption on whether all firms are affected equally by a policy measure, or whether they are affected differently.

4.3.1.1 Homogeneous treatment effects

We assume that we want to assess the impact of a policy intervention on some outcome variable *Y*. The outcome variable in our analysis below will be the innovation behavior measured by the innovation effort and the innovation output measured by the companies' likelihood to patent. We also assume that the outcome Y_i of a firm *i* depends not only on treatment through the policy intervention d_i=1, but also on exogenous factors X_i through the function *g*(.).

The dichotomous character of d_i corresponds to the information available in the data set. As discussed above, we can only utilize information on whether or not companies received treatment or not. We have no data on the intensity of the treatment. Note that, in the analysis to come, we interpret public funding and/or collaboration as treatments. Essentially, one could think of continuous treatments if the size of the subsidy or the intensity of the collaboration is available. If information on continuous treatments is available, the analysis of the impacts would have to employ a different set of approaches than the ones discussed in section 4.3.2 through 4.3.5.

As the intervention is carried out at a certain time, say *t*=*k*, we have to distinguish before and after the intervention:

$$Y_{it} = g(X_{it}) + d_i\alpha + U_{it} \quad \text{for} \quad t > k \tag{1}$$

$$Y_{it} = g(X_{it}) + U_{it} \quad \text{for} \quad t \leq k\,. \tag{2}$$

We talk about homogeneous treatment effects, since the effect of the treatment α does not vary across individuals.

However, if we assume that the treatment d_i is not random, but depends on some firm-specific characteristics that might also affect the outcome Y_{it}, the treatment d_i and the error U_{it} are not uncorrelated. If we cannot control for the underlying firm-specific effects, the standard OLS regression will not produce valid results.

We can conceptualize the participation decision as follows:

$$\delta_i = Z_i \gamma + V_i \tag{3}$$

and subsequently

$$d_i = 1 \text{ if } \delta_i > 0 \tag{4}$$
$$d_i = 0 \text{ otherwise.}$$

4.3.1.2 Heterogeneous treatment effects

If, in contrast to the assumption underlying the homogeneous treatment effects, we assume that the treatment effects vary across individual firms, then we deal with heterogeneous treatment effects. The treatment variable α in the outcome equation above has to be indexed for each firm *i* to give the firm-specific treatment effect.

$$Y_{it} = g(X_{it}) + d_i \alpha_i + U_{it} \quad \text{for} \quad t > k \tag{5}$$

If the average treatment effect of all companies is denoted $\overline{\alpha}$ and the average treatment effect of the treated companies is $\overline{\alpha}_T$ and the ε_i is the firms' deviation from the average treatment effect, then the firm-specific treatment effect can be written as $\alpha_i = \overline{\alpha} + \varepsilon_i$. The average treatment effect of treated companies can then be written as $\alpha_T = \overline{\alpha} + E(\varepsilon_i \mid d_i = 1)$. $E(\varepsilon_i \mid d_i = 1)$ is the expected mean deviation of the treated companies from the overall mean treatment effect. Then the outcome equation will take the following form:

$$Y_{it} = g(X_{it}) + d_i \overline{\alpha} + [U_{it} + d_i \varepsilon_i] = g(X_{it}) + d_i \overline{\alpha} + [U_{it} + d_i(\alpha_i - \overline{\alpha})]. \tag{6}$$

The last term in the squared brackets indicates an additional problem for identification as the error term $U_{it} + d_i(\alpha_i - \overline{\alpha})$ also differs across firms, depending on whether they are treated or not. If *g*(.) is a linear function and $E(\varepsilon_i d_i) \neq 0$ OLS identifies

$$E(\hat{\alpha}) = \overline{\alpha} + E(\overline{\varepsilon}_i \mid d_i = 1) + E(U_{it} \mid d_i = 1) - E(U_{it} \mid d_i = 0)\,. \qquad (7)$$

If U_{it} is not correlated to d_i such that $E(U_{it} \mid d_i = 1) = E(U_{it} \mid d_i = 0)$, there is still an identification problem. Only the treatment effect on the treated α_T can be identified as $\alpha_T = \overline{\alpha} + E(\varepsilon_i \mid d_i = 1)$.

4.3.2 Instrumental variable estimation

In the case of homogeneous treatment effects α, the instrumental variable (IV) method can identify the treatment effect, if there is at least one regressor Z^* in the decision rule in equation (3) which is not in the outcome regression equation (1) and equation (2). It has to satisfy three conditions:

(1) It determines the decision regression in the sense that the estimation results in a coefficient estimate which is significantly different from zero.

(2) Z^* can be transformed such that it does not correlate with the error term U_{it}, given the exogenous variables X.

(3) Z^* is not completely determined by X.

The IV approach suffers from two major shortcomings: First, it is hard to find an instrument Z* which satisfies all the three conditions stated above. In our case of public R&D funding, it is hard to think of a variable determining the selection of a firm or project for funding and not being correlated to the outcome of R&D. As we will see below, the available data essentially consists of cross-sectional data only. The common strategy, which is to use the lagged values of some determinant as instruments, cannot be pursued here.

The second drawback is even more severe. In the case of heterogeneous treatment effects, the error term is $U_{it} + d_i(\alpha_i - \overline{a})$ in equation (6). Even if we find an instrument Z^* which is uncorrelated with U_{it} it is not uncorrelated with $U_{it} + d_i(\alpha_i - \overline{a})$ because it determines d_i by definition. Therefore, the IV method cannot be applied in the case of heterogeneous treatment effects.

4.3.3 Diffs-in-diffs

The differences-in-differences approach is applicable when panel data or repeated cross section data are available. At least one data set before treatment and one data set after treatment have to be available, in which we denote the time before treatment t_0 and the point of time after treatment t_1.

The underlying idea of diff-in-diffs is compatible with the notion of natural experiments. It interprets the treatment itself as an experiment. The solution to the missing data problem is to find a natural control group. The difference-in-difference approach compares the difference in the mean outcome before and after treatment of the treated firms $\overline{Y}^T$ and the control group $\overline{Y}^C$. If we disregard other exogenous factors than the treatment indicator d_i the diffs-in-diffs approach leads to the following:

$$\hat{\alpha}_{did} = (\vec{Y}_{t_1}^T - \vec{Y}_{t_0}^T) - (\vec{Y}_{t_1}^C - \vec{Y}_{t_0}^C) \,. \tag{8}$$

In the case of heterogeneous treatment effects, the diffs-in-diffs estimator identifies the average treatment effect on the treated. Given $g(.)$ is linear we observe that

$$\begin{aligned} E(\hat{\alpha}) = [\beta + \alpha_T + E(U_{t_1} \mid d=1) - \beta - E(U_{t_0} \mid d=1)] - \\ -[\beta + E(U_{t_1} \mid d=0) - \beta - E(U_{t_0} \mid d=0)] = \alpha_T \end{aligned} \,. \tag{9}$$

This approach eliminates firm-specific effects and common macro effects. Yet, the selection of the natural control group proves rather difficult. This is even more the case, as it assumes that there are common time effects across the groups, and that the groups do not change their composition.

4.3.4 Heckman selection models

In contrast to the IV method, Heckman selection models (Heckman 1979) are more robust. They allow for the identification of the average treatment effect on the treated. However, they require more restricting assumptions on the structure of the model than the IV method does.

Again, the selection models require a regressor in the selection equation that obtains a significant parameter estimate and is uncorrelated to the error term of the selection equation. In addition, knowledge about the joint density distribution of the error term of the selection and the outcome equation is required. The general idea of the selection models is to control for the part of the error term that is directly related to the participation dummy.

We discuss the Heckman selection model only for the case of heterogeneous treatment effects. If we substitute $\alpha_T = \overline{\alpha} + E(\varepsilon_i \mid d_i = 1)$ into equation (6) we yield

$$Y_{it} = g(X_{it}) + d_i \alpha_T + \{U_{it} + d_i [\varepsilon_i - E(\varepsilon_i \mid d_i = 1)\} = g(X_{it}) + d_i \alpha_T + \zeta_{it} . \quad (10)$$

In the two-step procedure, we use the joint density of U_{it}, V_i and ε_i which we assume to be a joint normal distribution. The expected error term for the treated and non-treated firms becomes

$$E(\zeta_{it} \mid d_i = 1) = Corr(U_{it} + \varepsilon_i, V_i)\, Var(U_{it} + \varepsilon_i)^{0.5} \frac{\phi(Z_i \gamma)}{\Phi(Z_i \gamma)} = \rho_{(U,V,\varepsilon)} \frac{\phi(Z_i \gamma)}{\Phi(Z_i \gamma)} \quad (11)$$

$$E(\zeta_{it} \mid d_i = 0) = Corr(U_{it}, V_i)\, Var(U_{it})^{0.5} \frac{-\phi(Z_i \gamma)}{1 - \Phi(Z_i \gamma)} = \rho_{(U,V)} \frac{-\phi(Z_i \gamma)}{1 - \Phi(Z_i \gamma)} \quad (12)$$

Assuming $g(.)$ to be linear the outcome regression is then

$$Y_{it} = X_{it} \beta + d_i \left[\alpha_T + \rho_{(U,V,\varepsilon)} \frac{\phi(Z_i \gamma)}{\Phi(Z_i \gamma)} \right] + (1 - d_i) \rho_{(U,V)} \frac{-\phi(Z_i \gamma)}{1 - \Phi(Z_i \gamma)} + \vartheta_{it} . \quad (13)$$

We observe that α_T can be identified from this equation.

4.3.5 Matching

Unlike most of the above-discussed methods which identify the treatment effect by estimating the counterfactual, the matching approach does not require an assumption of functional specifications. It is non-parametric. However, as there is generally no free lunch, there is a trade-off between the functional specifications and other assumptions underlying the approach. Matching requires a strong set of the latter, though. The strongest assumption to ensure the validity of the matching estimator is the *conditional independence assumption* (Rosenbaum and Rubin 1983, Rubin 1977):

Let Y^T be the outcome of the treated firms and let Y^C be the outcome of the firms in the control group.

$$Y^T = g^T(X) + U^T \tag{14}$$

$$Y^C = g^C(X) + U^C . \tag{15}$$

Note that we assume that even the function $g(.)$ can vary between the treated firms and firms in the control group. The matching estimator tries to estimate the effect of treatment on the treated α_T by comparing their outcome with the outcome of the counterfactual:

$$\alpha_T = E(Y^T - Y^C \mid X, d = 1) . \tag{16}$$

The conditional independence assumption states that given the exogenous and observable characteristics *X*, the non-treated firms' outcome is the same as the treated firms' outcome, had the treated not been treated. Phrased differently, the selection only occurs on observables:

$$Y^C \perp d \mid X . \tag{17}$$

Additionally, both the treatment group and the control group have to have a common support. This condition is illustrated in section 6.2.3.2 below.[22]

The procedure to carry out a matching generally takes an observation *i* in the treated sub-sample and finds an observation *j* where $\left\| X_i - X_j \right\|$ is minimized. Matching approaches differ according to whether *j* is an observation taken from

[22] In particular see page 158.

the sample of non-treated firms or artificially composed from the set of non-treated firms. They also vary according to the metric $\| \|$ used. Below we will use a kernel-based matching where *j* is constructed as a convex combination of all firms in the non-treated sample, and the weights for each firm indicate dissimilarity with firm *i*.[23] We will also use a nearest-neighbor matching, where firm *j* is the observation which is nearest (most similar) to firm *i* in the *X* space. In both cases, we will use the Mahalanobis metric to measure similarity.

However, it is evident that the larger the set of exogenous characteristics in *X*, the harder it is to find an appropriate observation *j* to match the given characteristics of an observation *i*. This phenomenon is vividly phrased as the *curse of dimensionality*. An elegant and therefore extremely workable solution to the problem is offered by Rosenbaum and Rubin (1983 and 1984). They show that the matching assumptions

$$Y^C \perp d \mid X \quad (18)$$

[24]

ensure the conditional independence assumption, even when controlling for the propensity score of *X* instead of controlling for *X* directly.

4.4 Summary

In the previous sections we discussed the instrumental variable estimation, the difference-in-difference estimators, the Heckman selection models and the matching estimators as potential approaches to deal with the evaluation problem when non-experimental data is available.

The IV estimator is found to be unsuitable for the research questions posed in this research. All other approaches have their advantages, as well as their shortcomings. In the following sections we will base our main arguments on empirical findings which we obtain by employing the matching estimator.

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[23] Kernel-based matching is used in section 5 below.

[24] And additionally $0 < P(d=1|X) < 1$.

However, we will not restrain ourselves to the application of a single methodology. We will supplement our analysis with Heckman selection models in the discussion in section 5 and by a variant of the diffs-in-diffs estimator in section 6. Table 4-3 summarizes the mix of methodologies used in the empirical analysis below.

Table 4-3. Method mix for the analyses to come.

	Description	Input additionality Section 5	Output additionality Section 6
Instrumental variable estimator	Section 4.3.2	–	–
Diffs-in-diffs	Section 4.3.3	–	X
Heckman selection models	Section 4.3.4	X	–
Matching	Section 4.3.5	X	X

All the used methodologies require three different types of firm-level information. Information on the outcome variable *Y*, the treatment indicator *d* and the exogenous firm characteristics *X*. The analysis will use innovation expenditure and patent applications as the outcome variables. It will use the receipt of public subsidies, collaboration for innovation, or both, as the treatment indicator. The exogenous firm-level characteristics will be filled with variables such as size, sector, export, focused markets, etc.

5. Input additionality

_______ This section presents an empirical analysis of the effects of public subsidies on the innovation input of subsidized firms. After an extensive exploratory analysis, the matching approach is used to assess the impacts of public funding on the R&D expenditure of funded firms in Finland. Two different assumptions will be analyzed, giving rise to upper and lower boundaries of the effect. Studies for German samples of firms are compared to the results obtained here. Finally, the sensitivity of the results to the choice of methodology is checked by employing Heckman selection models for the estimation of the impact. ____

5.1 Introduction

Following the literature on input additionality, we analyze how the receipt of public subsidies for innovation activities affects the level of these activities. The analysis is conducted at the level of the funded firm. We estimate the effect that public funding has on funded firms. At this stage we do not analyze the effect that public funding could have on firms that have not received governmental support for their R&D. Hence, the emphasis is on assessing the effect of the actual policy measures, rather than assessing that of potential policy.

Additionally, we are only looking at the effectiveness of governmental support for R&D. We cannot assess whether or not there are other potential policy measures which could achieve a comparable set of effects at a lower cost, or a higher level of effects at the same cost. Therefore, we are not concerned with the efficiency of public funding for R&D.

First, we analyze the effect public funding has on the R&D expenditure of funded Finnish firms. After introducing the data and delivering an exploratory analysis, we use the matching approach to construct the counterfactual situation and to finally estimate the input effect of public funding. We estimate upper and lower boundaries for the effect. Subsequently, we compare the results with the effects estimated on comparable German data. Finally we check the robustness of the results by employing Heckman selection models.

Summarizing the results, we find strong and robust evidence for the positive input effects of public funding. Even subtracting the subsidies, funded firms spend more on innovation activities than they would have spent without the subsidies. The lower boundaries of the effects estimated here are in accordance with the findings for the German data.

5.2 Data

The data used for the analysis in this section utilizes data from the CIS II and the CIS III. Hence it covers the years 1994 to 1996 and 1998 to 2000. This data is complemented with data taken from Statistics Finland’s patent data base and its employment register. Table 5-1 contains the descriptive statistics for the whole set of 2,462 observations. We use the year 1996 to indicate data taken from CIS II, and the year 2000 to indicate data taken from CIS III.

Table 5-1. Descriptive statistics (N = 2,462).

Description	Mean	St. dev.	Min	Max
Employment[1*] (in 1,000)	0.141	0.258	0.010	2.474
Employment squared[1*]	0.087	0.389	0.000	6.123
Share of highly educated employees[2]	0.312	0.252	0.000	1.000
Share of highly educated employees squared[2]	0.161	0.251	0.000	1.000
Prior patenting activity[3] (from 1985 onwards)	0.189	0.392	0.000	1.000
Export as share of sales[1*]	0.276	0.290	0.000	1.000
Severe hampering factors[1] (dummy)	0.308	0.461	0.000	1.000
Year 2000[1] (dummy)	0.502	0.500	0.000	1.000
Innovative activities[1] (dummy)	0.560	0.498	0.000	1.000
R&D intensity[1] (net of av. subsidies[3])	0.026	0.100	0.000	1.000
Share of R&D employees[1+]	0.017	0.054	0.000	0.769
Share of R&D employees squared[1+]	0.003	0.018	0.000	0.592
Public funding[1+] (dummy)	0.264	0.440	0.000	1.000

Note: Data sources: [1] CIS II and CIS III. 2 Statistics Finland's employment register. [3] Statistics Finland's patent statistics. [4] Information from the National Technology Agency (Tekes) used to estimate the size of the average subsidy. [5] Commercialized product or process innovations on the market. * The employment and the export share are the average of the variables between 1994 and 1996 for CIS II and between 1998 and 2000 for CIS III. + Only for companies which carry out innovative activities. The sample contains only companies with a minimum of 10 and a maximum of 2,500 employees.

5.2.1 All companies

The companies in the data set are subdivided into four size classes based on a headcount of their employees. It reflects the definition of SMEs used by the European Commission (European Commission 2003) and the definition used by the Finnish National Technology Agency (Tekes) within their funding programs (Tekes 2005a). Small and medium sized companies employ fewer than 250 people, whereas small companies employ fewer than 50 employees. In our classification, large companies are subdivided into companies with fewer than

500 employees and those with 500 or more employees. Table 5-2 displays the distribution of the companies across the size classes.

Table 5-2. Frequency and distribution of companies based on size.

Size Class	Employees	1996		2000	
Small	(<=49)	620	51%	673	54%
Medium	(50–249)	420	34%	423	34%
Large	(250–499)	102	8%	85	7%
Large	(>=500)	80	7%	59	5%
Total		1222	100%	1240	100%

Across the two years of observation we see a comparable distribution of size classes in the sample. The largest class is the smallest in size; more than half the companies employ fewer than 50 employees. About a third of the companies employs between 50 and 249 employees. The smallest classes in terms of employee numbers are the largest in size.

Table 5-3. Sectoral distribution of companies in the sample.

Size Class	Employees	High technology sector	Low technology sector	Knowledge intensive services	Total
Small	(<=49)	27%	56%	18%	100%
Medium	(50–249)	31%	55%	14%	100%
Large	(250–499)	36%	53%	11%	100%
Large	(>=500)	32%	60%	7%	100%

Note: High technology sectors are the “High technology manufacturing sectors” and the “Medium high technology manufacturing sectors” according to Hatzichronoglou (1997). Low technology sectors are all other manufacturing sectors. The knowledge-intensive services are the post and telecommunication services and business activities (NACE 72-74).

The sectoral distribution of the companies is displayed in Table 5-3, where, for reasons of parsimony, we only report aggregated sectoral categories. We use the definition of sectoral knowledge-intensity as laid out in Hatzichronoglou (1997) to compose high and low technology sectors. For classification purposes, we neglect the medium-high and medium-low technology sectors and lump them together with the high and low technology sectors, respectively. Our sample also contains companies from knowledge-intensive service sectors such as post and telecommunications and business activities (NACE 72-74), excluding real estate services.

We observe that across size classes the sectoral distribution is quite homogeneous. About 30 percent of the companies in each size class are classified as high technology manufacturing. About 55 percent to 60 percent are from low technology sectors. Only the knowledge-intensive services are represented less in the class of the largest companies than they are in the other size classes. Knowledge-intensity can also be approximated by the fraction of highly educated employees in the firms. Table 5-4 breaks down the percentage of highly educated employees by the sectoral affiliation of the companies and their size.

Table 5-4. High educated employees.

Size Class	Employees	High technology sector	Low technology sector	Knowledge intensive services
Small	(<=49)	30%	18%	68%
Medium	(50–249)	34%	23%	62%
Large	(250–499)	39%	25%	61%
Large	(>=500)	32%	27%	57%

Note: The average percentage of employees with a university or polytechnic education and above. High technology sectors are the “High technology manufacturing sectors” and the “Medium high technology manufacturing sectors” according to Hatzichronoglou (1997). Low technology sectors are all other manufacturing sectors. The knowledge-intensive services are the post and telecommunications services and business activities (NACE 72-74).

Here, also, we observe that the firm characteristics are rather homogeneously distributed across the firm-size classes. Large companies with major activities in low technology sectors seem to employ a higher percentage of highly educated employees than the smaller firms do. Companies with the largest percentage of highly educated employees are from the knowledge-intensive service sectors. The percentage of highly educated employees there is about twice as large as it is in the high technology manufacturing sectors.

For all companies – not only for innovating companies – we included some indicators which provide information about their innovation activities and obstacles. Table 5-5 reports the percentage of companies with previous patenting activity and the percentage of companies reporting severe hampering factors concerning innovation activities.

Table 5-5. Hampering factors and patenting activity.

Size Class	Employees	Severe hampering factors	Previous patenting activity
Small	(<=49)	30%	11%
Medium	(50–249)	31%	25%
Large	(250–499)	29%	34%
Large	(>=500)	31%	52%

Note: Percentage of companies reporting severe hampering factors for their innovation activities and percentage of firms with previous patenting experience.

Across size classes we observe no variation in the percentage of companies experiencing severe hampering factors. This observation seems to contradict the observation in Ebersberger (2004a) that larger companies tend to report more severe hampering factors. However, there are slight differences that may cause the divergent observations. The observation in Ebersberger (2004a) is based on data for innovating companies in the year 2000. In the data from the year 1991 (CIS 1) there is no such relationship. In contrast, here we use data covering innovating as well as non-innovating companies from the years 1996 and 2000. Furthermore, the descriptive Table 5-5 does not take other factors such as sectoral affiliation into account.

Previous[25] patenting activity approximates previous innovation activity. Not surprisingly, the larger the company, the more likely it is that it had previous innovation activity before the year of observation.

Current innovation activity is covered in Table 5-6. The larger the size of the company, the more likely it is that the company carries out innovation activities, which is a plausible result. If the size of a company in terms of employees is an indicator of its level of activity, and if there is a constant probability to carry out innovation activities per unit of activity, we observe that larger companies are more likely to carry out innovation activities than smaller companies.

Table 5-6. Innovating companies.

Size Class	Employees	High technology sector	Low technology sector	Knowledge-intensive services	All sectors
Small	(<=49)	53%	38%	58%	45%
Medium	(50–249)	77%	49%	67%	60%
Large	(250–499)	96%	74%	70%	81%
Large	(>=500)	89%	85%	90%	86%

Note: The percentage of innovative companies by size classes and sector. The definition of innovating companies is given in section 5.2.2 on page 102 below.

Not surprisingly, across all size classes the low technology sector is the one with the lowest rate of innovators.

Let us consider those companies that neither commercialize innovations nor carry out innovation projects (be they ongoing or abandoned). If we assume that such companies do not spend resources on innovation, we can suppose that their innovation expenditure is zero. Based on this assumption, we can report the following innovation intensities for firms.

[25] In our observations for previous patenting activities we go back to the year 1985.

Table 5-7. Average innovation intensity.

Size Class Employees		High technology sector	Low technology sector	Knowledge-intensive services	All sectors
Small	(<=49)	6.0%	1.7%	10.2%	4.3%
Medium	(50–249)	4.1%	1.5%	6.6%	3.0%
Large	(250–499)	4.8%	1.8%	8.2%	3.6%
Large	(>=500)	5.8%	1.3%	2.4%	2.9%
Over all		5.2%	1.6%	8.7%	3.7%

Note: The average innovation intensity by size and sector. The innovation intensity is the percentage of sales spent on innovation activities.

The average innovation intensity measured by the percentage of sales spent on innovation activities is shown in Table 5-7. On average, the companies in the sample spend about 3.7 percent of their sales on innovation activities. Not surprisingly, low technology companies spend the least and knowledge-intensive companies spend the most on innovation activities. The innovation survey includes various categories of expenditure related to innovation activities. Table 5-8 gives an impression of the categories alluded to in the CIS questionnaires.

Table 5-8. Categories of expenses related to innovation activities.

Category	Description
Intramural research & experimental development (R&D)	All creative work undertaken within your enterprise on a systematic basis in order to increase the stock of knowledge, and the use of this stock of knowledge to devise new applications, such as new and improved products (goods/ services) and processes (including software research)
Acquisition of other external knowledge	Purchase of rights to use patents and non-patented inventions, licenses, know-how, trademarks, software and other types of knowledge from others for use in your enterprise's innovations
Training	Internal or external training for your personnel directly aimed at the development and/or introduction of innovations
Market introduction of innovations	Internal or external marketing activities directly aimed at the market introduction of your enterprise's new or significantly improved products (goods/services), (may include preliminary market research, market tests and launch advertising, but exclude the building of distribution networks to market innovations)
Design, other preparations for production/deliveries	Procedures and technical preparations to realize the actual implementation of products (goods/services) and process innovations not covered elsewhere

Note: The definition is taken from the CIS III Eurostat core questionnaire (Eurostat 2001, p. 6) which is also reproduced here in Appendix A.

5.2.2 Innovating companies

In this section we focus only on innovating companies. Companies are denoted *innovating*, if they report the commercialization of a product innovation or the introduction of a process innovation in the years covered by the survey. A company is also denoted *innovating*, if it reports an ongoing innovation project or an abandoned innovation project in the years covered. The distribution of innovation activities in each size class is reported in Table 5-9.

Table 5-9. Distribution of innovation activities.

Size Class Employees		Product[1]	Process[2]	Project[3]	Product[1] & Process[2]	Process[2] & Project[3]	Product[1] & Project[3]	Prod [1] Proc[2] & Proj.[3]
Small	(<=49)	20%	9%	15%	14%	3%	20%	19%
Medium	(50–249)	10%	7%	13%	8%	5%	24%	32%
Large	(250–499)	7%	5%	14%	7%	5%	22%	40%
Large	(>=500)	3%	1%	6%	5%	3%	19%	63%

Note: All columns are mutually exclusive. [1] Company commercialized a product innovation. [2] Company introduced a process innovation. [3] Company carried out an ongoing or abandoned innovation project.

About 20 percent of the innovating companies with fewer than 50 employees commercialize a product innovation, but neither introduce a process innovation nor carry out ongoing or abandoned innovation projects. As company size increases, the percentage of companies introducing only product innovations decreases to 3 percent (the size class with the largest companies). The same observation holds for process innovations and ongoing or abandoned innovation projects. 14 percent of the smallest companies report product innovation and project innovations simultaneously, but at the same time no ongoing or abandoned innovation projects are reported. The percentage of companies with process innovation and ongoing or abandoned innovation projects remains constant across the size classes. Also, the percentage of companies reporting no process innovations, but product innovations and ongoing projects remains around 20 percent over all size classes. The percentage of companies with ongoing or abandoned projects, commercialization of product innovations and the introduction of process innovations increases with the size of the company from about 20 percent to over 60 percent.

As already pointed out above, the particular layout of the survey questionnaire of the CIS creates certain variables only for innovating companies. The information which is only available for innovating companies includes data on R&D employees, information on innovation output such as patents or the percentage of sales generated by new products and services. For the time being and for this analysis, we disregard the latter and summarize the former in Table 5-10.

Table 5-10. Characteristics of innovating firms.

Description	Mean	St. dev	Min	Max
Share of R&D employees	0.017	0.054	0.000	0.769
Share of R&D employees squared	0.003	0.018	0.000	0.592
Patenting (dummy)	0.288	0.450	0.000	1.000

About 1.7 percent of the employees in innovating firms are labeled as R&D personnel. Note also that there are some firms where innovation activities are carried out without any R&D employees. About 29 percent of the innovative companies report patenting activity for the years under observation.

Table 5-11. Average innovation intensity of innovating firms.

Size Class	Employees	High technology sector	Low technology sector	Knowledge-intensive services	All sectors
Small	(<=49)	11.2%	4.5%	17.5%	9.5%
Medium	(50–249)	5.3%	3.0%	9.8%	4.9%
Large	(250–499)	5.1%	2.5%	11.7%	4.4%
Large	(>=500)	6.6%	1.6%	2.7%	3.3%
Over all		7.6%	3.4%	14.0%	6.7%

Note: The average innovation intensity of innovating companies by size and sector. Innovation intensity is a percentage of sales spent on innovation activities.

In Table 5-11 we give an overview of the distribution of the intensity of innovation activities across sectors and firm-size classes. In line with what we observed for all companies in Table 5-7 above, we see that, by and large, the innovation intensity of innovating companies is the lowest in low technology sectors and the highest in knowledge-intensive service firms. High technology firms with more than 500 employees tend to spend more on innovation than their counterparts in the knowledge-intensive service sectors. On average, innovating companies with fewer than 50 employees spend more than 9 percent of their sales on innovation activities. As we move up the company size classes, the innovation intensity decreases to around 3.3 percent.

5.3 Exploratory analysis

The observations above refer to the overall spending of companies on innovation activities. They do not yet distinguish between private sources of funds and public sources of funds such as R&D subsidies. Between 13 percent and 66 percent – depending on the year and the size class – of the observed innovating companies receive public support for their innovation activities. Table 5-12 displays the percentage of companies in the sample which receive public funding. The larger the companies, the higher is the percentage which receive public subsidies for their innovation efforts. Table 5-12 also reveals that, across all size classes, the percentage of companies receiving funding is larger in the 2000 survey than in the 1996 survey.

Table 5-12. Distribution of funded companies.

Size Class	Employees	1996 funded	2000 funded	All years
Small	(<=49)	34.5%	50.1%	44.0%
Medium	(50–249)	40.9%	50.4%	46.2%
Large	(250–499)	44.3%	68.5%	55.9%
Large	(>=500)	67.2%	73.6%	70.0%
All size classes		41.8%	53.6%	48.4%

Note: Percentage of companies receiving public funding for their innovation activities.

As the CIS questionnaires ask about public funding for R&D only in the case of innovating companies, we have to assume that there are no funded companies among the non-innovating companies. So we can restrict the exploratory analysis to innovative companies. The key question of this section is to analyze the input additionality of public funding. So we will concentrate mainly on the input in the innovation activities of firms. (See Table 5-13.)

Table 5-13. Innovation intensity of innovative companies.

Size Class Employees		Funded companies	Non-funded companies	All
Small	(<=49)	15.2%	5.0%	9.5%
Medium	(50–249)	6.5%	3.6%	4.9%
Large	(250–499)	6.3%	2.0%	4.4%
Large	(>=500)	3.8%	2.1%	3.3%
All size classes		9.6%	4.0%	6.7%

Note: The average innovation intensity by size and funding. Innovation intensity is a percentage of sales spent on innovation activities.

We observe strong differences between funded and non-funded companies in innovation expenditure relative to the companies' sales. For the smallest companies, the difference amounts to more than 10 percentage points. This difference decreases to about 1.7 percentage points for the largest companies.

If there was random assignment of subsidies to companies, and if companies substituted public subsidies for private innovation effort, we would not observe strong differences between funded and non-funded companies. Hence, the above observation suggests that, either there is no random assignment, or there is no indication of complete substitution. However, we have to analyze the observed difference more thoroughly.

Even if there is no complete substitution, we could still suspect that companies partially substitute public funding for their private innovation effort. To analyze this, we have to know or estimate the size of the subsidy. As the amount of money received by the company is not covered in the innovation survey data, we have to resort to additional information. In Ebersberger and Lehtoranta (2005) we use funding information for cooperative R&D supplied by the National Technology Agency. From this we can estimate the average number of subsidized projects simultaneously run by a company of a certain size class in the years 1996 to 1999. It is summarized in Table 5-14.

Table 5-14. Number of simultaneously subsidized projects.

Size Class	Employees	No. of projects
Small	(<=19)	1.12
Medium	(20–99)	1.17
Large	(100–499)	1.43
Large	(>=500)	1.92

Note: The size classes of the SMEs have been changed to make them compatible with the information supplied about the size of the subsidy.

The information contained in the annual reports of 1996 and 2000 of the National Technology Agency (Tekes 1997, 2001) enables us to estimate the average subsidy for the size classes already used in Table 5-14. Table 5-15 reports the estimated average subsidies.

Table 5-15. Average size of the subsidy.

Size Class	Employees	1996	2000
Small	(<=19)	100	144
Medium	(20–99)	133	188
Large	(100–499)	158	230
Large	(>=500)	247	344

Note: The average size of the subsidy is computed from information on the whole volume of subsidies for R&D, the number of funded projects in each size class and the amount spent for each size class.

Although the estimates are based on a rather rough set of information, they allow for computing the companies innovation expenditure net of the subsidies in Table 5-16. The differences in innovation intensity of the funded and non-funded firms decreases once we correct for the subsidies received. As the absolute size of the overall innovation expenditure is smaller for companies in the smallest size class, the reduction in the difference between innovation intensity in the funded and non-funded companies is most remarkable in this size class. The difference decreases from more than 10 percentage points to about 2.1 percentage points. For the largest companies the difference between funded and non-funded companies literally does not decrease.

Table 5-16. Private innovation expenditure net of subsidies.

Size Class	Employees	Funded companies	Non-funded companies	All
Small	(<=49)	7.1%	5.0%	5.9%
Medium	(50–249)	4.8%	3.6%	4.1%
Large	(250–499)	5.8%	2.0%	4.2%
Large	(>=500)	3.6%	2.1%	3.1%
All size classes		5.7%	4.0%	4.8%

Note: This table reports the private innovation intensity i.e. the innovation expenditure net of subsidies as a percentage of sales.

The difference in innovation intensity may be caused by an additionality effect or by the fact that funded and non-funded companies are so different that no comparison whatsoever is admissible. Let us turn to the latter and examine whether funded and non-funded firms have different characteristics.

In the upper part of Table 5-17 we analyze the differences in the characteristics of funded and non-funded firms. A univariate analysis suggests that funded companies are significantly larger, have more previous experience and a higher export orientation than non-funded companies. Funded companies also employ a higher percentage of R&D employees. The difference is not significant at the 5 percent level, though.

Table 5-17. Differences between funded and non-funded firms.

	Funded companies	Non-funded companies	Sig.
Size (in 1,000 employees)	0.223	0.132	***
Share of RD employees	0.018	0.016	
Previous patenting	0.377	0.184	***
Export orientation	0.397	0.268	***
High tech. manufacturing	44%	28%	***
Low tech. manufacturing	41%	53%	***
Knowledge-int. services	15%	19%	*

Note: ***(**,*) indicate significance at the 0.1% (1%, 5%) level.

The lower part of Table 5-17 contains the distribution of companies over the three sectors. About 44 percent of the funded firms are from high technology manufacturing sectors. This percentage differs significantly from the percentage of firms from high technology manufacturing sectors among the non-funded companies, which amounts to 28 percent. Firms from low technology manufacturing services are more represented among the non-funded companies than they are among the funded companies. The same holds true for firms from knowledge-intensive service sectors. This difference is not due to differing propensities to innovate in certain sectors, as we are looking only at innovating firms thus far in the analysis.

The univariate analysis must be augmented with a multivariate analysis, in which we regress the indicator for public funding on a set of company characteristics.

Table 5-18. Firm characteristics and funding.

	Estimate	Std.err.	Sig
Intercept	–1.22594	0.19345	***
Size (in 1,000 empl.)	0.87908	0.53597	
Size (squared)	0.1312	0.39342	
Share of R&D empl.	9.90942	3.63036	**
Share of RD empl. (squ.)	–28.02937	12.86919	*
Previous patenting	0.63968	0.14094	***
Export orientation	0.94995	0.21286	***
Observations	1369		
Obs (funding = 1)	663		
Obs (funding = 0)	706		
Chi2 (15)	177.3***		
Pseudo R2	0.156		

Note: The exogenous variables also contain nine industry dummies and one time dummy not reported here. *** (**, *) indicates significance at the 0.1%,(1%, 5%) level.

Table 5-18 reports the results of a logit regression of the public funding dummy variable on company characteristics such as size, R&D intensity, previous experience and export orientation. In addition to the variables reported we included a time dummy to differentiate the years 1996 and 2000 and nine industry dummies[26]. In the multivariate analysis we find some results contradicting the findings in the univariate analysis. If everything else is equal, we observe no difference in company size between funded and non-funded, yet innovating, firms. However, funded firms more frequently have previous patenting experience and a higher export orientation. Up to a threshold of 17 percent of R&D employees, the likelihood of receiving funding increases with the share of R&D employees. Beyond 17 percent, the likelihood decreases.

[26] The definition of the industry dummies can be found in Appendix B on page B1 below.

The upshot of Table 5-18 is that funded and non-funded companies are not comparable. The differences in the characteristics can be a result of the funding principles of the funding agencies, i.e. company proposals are evaluated in the light of a set of company-level criteria. This selection bias has to be accounted for when evaluating the impact of public funding on the innovation expenditure of funded companies.

5.4 Assessing input additionality

This section analyses the input additionality of public funding as a form of governmental intervention in innovation. In the following section we discuss the matching process. Then we differentiate the analysis based on two different assumptions on the effect of public funding. First we assume that public funding has an effect on the R&D status of companies, i.e. public funding also influences whether companies carry out innovative activities at all. Then we assume that the R&D status is unaffected by the receipt of subsidies. The first assumption will yield the upper boundary of the impact of public funding whereas the second assumption will yield the lower boundary.

5.4.1 Matching

For this analysis we employ the kernel-based variant of the matching approach. The matching procedure requires some considerations before being applied. First we have to define the sub-sample from which the control group will be constructed. Second we have to define the set of matching criteria.

5.4.1.1 Control group

Basically the sample from which the control group is constructed consists of non-funded companies. However, the sample can contain all non-funded companies regardless of innovation activities, or it can contain all non-funded but innovating companies.

If we assume that the decision to carry out innovation activities is a strategic decision of the firm, it is likely to be unrelated to the positive funding decisions of the funding agency. In this case we must assume that even non-funded companies come to a positive decision to carry out innovation activities. The sample from which we construct the control group contains innovating but non-funded firms.

Czarnitzki (2002) points out that funding not only affects the amount spent on innovation activities, but may also change the R&D status. In the presence of financial constraints, public R&D subsidies may enable a company to start doing R&D. This is even more relevant for small and micro firms. The correct control group in this case is constructed from all non-funded firms, regardless of their innovation activities. As neither line of reasoning can be rejected on the grounds of plausibility considerations, we conduct the analysis for both types of control groups. Section 5.4.2 presents an analysis in which the control group is constructed from all non-funded companies regardless of their innovation activities. Then section 5.4.3 reports an analysis in which the control group is constructed from all non-funded but innovating companies.

5.4.1.2 Matching criteria

In selecting the set of matching criteria, we have to make sure that the sample of funded firms and the matched sample of non-funded firms are comparable. In considering the idea of propensity score matching, the first choice is to select the propensity to receive funding as a matching criterion. Additionally, since public funded firms are exclusively companies with innovation activities, the matched companies should be comparable in their propensity to carry out innovation activities. The data source we use for this analysis consists of two pooled cross sections. Hence, the year of the observation has to be included in the matching process to ensure that a company from the 2000 sample is not matched with a company from 1996. This requirement is strictly enforced. In addition, a discussion of the size and size classes requires that the matched companies are comparable in size. The matching criteria are hence:

(1) propensity to carry out innovation activities

(2) propensity to receive public funding

(3) year of observation

(4) size of company.

The year of observation and size of company in terms of numbers of employees can be taken from the data directly. The propensity to carry out innovation activities and the propensity to receive public funding has to be estimated through a regression analysis. Public funding is only observed for companies with innovation activities. Hence, we cannot compute the propensity to receive funding and the propensity to carry out innovation activities by means of two unrelated probit regressions. We must control for the selection that is incorporated in this design. We use a probit regression with a sample selection (Heckman Probit) to compute the propensity scores for innovation activities and for public funding simultaneously.

5.4.1.3 Matching procedure

Before we proceed with the matching approach, we must identify the companies' propensity to carry out innovation activities and their propensity to receive public funding for their innovation activities. Table 5-19 summarizes the matching procedure.

Table 5-19. Matching protocol.

Step 1	Specify and estimate a Heckman probit model to obtain the propensity scores.	
Step 2	Restrict the sample to common support: delete all observations among the funded firms with probabilities larger than the smallest maximum and smaller than the largest minimum of the non-funded firms.	
Step 3	Estimate the counterfactual expectations of the R&D input variables for the funded companies.	
	a)	Choose one observation in the sub-sample of the funded companies and delete it from the pool.
	b)	Generate an observation as a convex combination of all companies in the sub-sample of non-funded companies. Determine the weights for the convex combination based on the Mahalanobis distance in the space of the matching characteristics. Add the generated observation to the group of matched comparisons.
	c)	Repeat a) and b) until no observation is left in the sub-sample of funded companies.
	d)	Using the matched comparison group formed in c), compute the respective conditional expectation by the sample mean.
Step 4	Compute the estimate of the treatment effects using the results of Step 4.	

Table 5-20 reports the coefficient estimates and the estimated marginal effects. Concerning the probability to carry out innovation activities, the size of the company has an inverse u-shaped influence. For the sample used here, the likelihood to carry out innovation projects decreases from 1,330 employees on. However, the particular impact of the size may be influenced by the fact that we restricted the sample to companies with fewer than 2,500 employees. The knowledge intensity also shows an inverted u-shaped influence. Beyond approximately 60 percent of highly educated employees, the likelihood to carry out innovation activities decreases. The export orientation of a company increases its propensity to be innovation-active. Companies reporting severe factors which hamper their innovation activities have a significantly lower (20.5 percent) probability to be product- or process-innovative or to carry out innovation projects.

Table 5-20. Heckman-probit estimation (N = 2,462).

Variables	Coef.	Std.err.	Marg.eff
Public funding			
Intercept	–0.539 *	0.268	
Employees	0.435	0.381	0.173
Employees (squared)	0.131	0.226	0.052
Share of R&D employees	6.159 **	2.189	2.454
Share of R&D employees	–17.634 *	7.728	–7.026
Prior patenting activity	0.379 ***	0.084	0.150
Export as share of sales	0.527 ***	0.158	0.210
Innovation activities			
Intercept	–0.890 ***	0.100	
Employees	2.501 ***	0.278	0.974
Employees squared	–0.939 ***	0.171	–0.366
Share of highly educated	3.557 ***	0.456	1.385
Share of highly educated	–2.924 ***	0.431	–1.139
Severe hampering factors	–0.523 ***	0.061	–0.205
Export as share of sales	0.863 ***	0.110	0.336
Disturbance correlation	–0.733 ***	0.088	
Num. of obs.	2,541		
Num. of obs. (innov=1)	1,438		
$Chi^2(15)$	68.97 ***		
Log likelihood	–2330.56		

Note: The exogenous variables also contain nine industry dummies and one time dummy not reported here. ***(**, *) indicates significance at the 0.1%,(1%, 5%) level.

Once companies carry out innovation activities, the firm size has no impact on the funding probability. The percentage of R&D employees among the companies' employees exerts an inverted u-shaped influence on the funding probability. Previous technological experience measured by the patent history dummy enters positively and increases the probability for public funding by 15 percentage points. The companies export orientation also has a positive impact on the probability to receive funding.

These findings are in line with the funding principles of the National Technology Agency (Tekes) as the major Finnish technology financing agency. Apart from the technological characteristics of the proposed technology, a positive decision for funding hinges on several characteristics of the applying firm such as the company's competitiveness, growth and resources. In a small open economy, the percentage of turnover generated by exports is an indicator of the competitiveness of the firm. The accumulated technological experience and number of R&D employees clearly indicate the resources spent on innovation.

An essential step in the matching analysis is to establish common support as indicated in step 2 of the matching protocol in Table 5-19. The following excursus illustrates the process of establishing common support.

Excursus: common support

To get an idea of what common support means, take for example a matching exercise with one matching criterion. Common support requires that at least the maximum of the matching criterion in the sub-sample of the treated observations is smaller than the maximum of the matching criterion in the sub-sample of the non-treated observations. At the same time, it requires that the minimum of the matching criterion in the sub-sample of the treated observations is larger than the minimum of the criterion in the sub-sample of the non-treated observation. If the common support condition is violated, no consistent estimation can be performed by the matching approach.

Figure 5-1 and *Figure 5-2* illustrate the violation of the common support assumption and how it can be re-established. The horizontal line indicates the axis along which the matching criterion is graphed. The crosses indicate the non-treated observations and the dots indicate the values of the matching criterion for the treated observations.

Figure 5-1 illustrates the complete violation of the common support condition. The maximum of the matching criterion in the sample of the treated observations is larger than the maximum of the matching criterion in the sample of the non-treated observations. As the minimum in the sample of the treated observations (the dot furthest to the left) is larger than the maximum in the sample of the non-treated observations (the cross furthest to the right), deletion of certain observations cannot re-establish the condition.

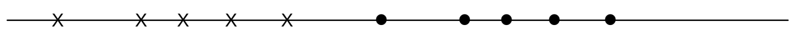

Figure 5-1. Illustration of violation of the common support condition.

Figure 5-2 also illustrates the violation of the common support condition in the upper section of the figure. However deletion of certain observations can re-establish the common support. Deleting the circled observations results in a sample where the matching criterion in the sample of treated observations and the matching criterion in the sample of non-treated observations have a common support (bottom section of *Figure 5-2*).

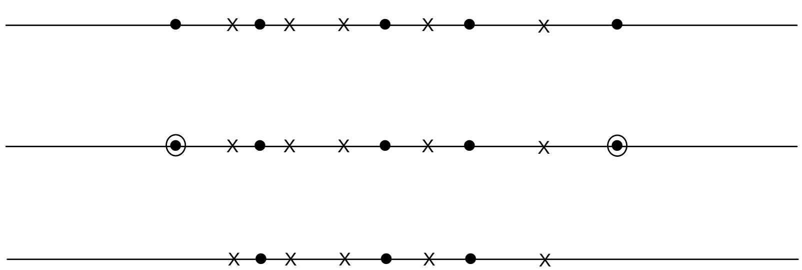

Figure 5-2. Illustration of re-establishing common support.

The common support condition can be re-established by deleting certain observations from the sub-sample of the treated observations. It may be argued that this is a shortcoming of the

> matching approach, in that it requires pruning of the sample of treated observations.[27] However, the deletion of observations is the price to pay to ensure comparability after the matching process. Note also that the observations are deleted on the basis of their exogenous characteristics and not on the basis of their endogenous features.

5.4.2 Matching with all companies

In this section we report the results of an impact analysis in which we assume that, for firms, the decision to receive funding fundamentally affects the their strategic decisions to carry out innovation activities. Some funded companies may not have carried out innovation activities if they had not received public funding. The funded companies' counterfactual estimated from non-funded companies must reflect this assumption. Hence, it is constructed from innovating, as well as from non-innovating, companies which have not received public funding. The correction of the selection bias is crucial to overcome the distortion in the analysis of firms' innovation spending that may be caused by the differences in company characteristics. By applying the matching approach and using company characteristics, we correct only for selection on observables such as company characteristics. We cannot control for the selection on non-observables. This is certainly a limitation of the matching approach. However, we are convinced that given the data and the research question at hand, we are correcting for much of the selection bias in the data. Furthermore, our approach is supported by Fier et al. (2004). The results they obtain with matching and sample selection models are remarkably similar. Below we will also check the robustness of our results obtained by the matching methodology against the results from selection models.

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[27] Note that, as indicated above, we use all possible combinations of funding and collaboration both as treatment and control. Hence, further down, the deletion of some companies which are not funded and do not collaborate is in line with the argument here.

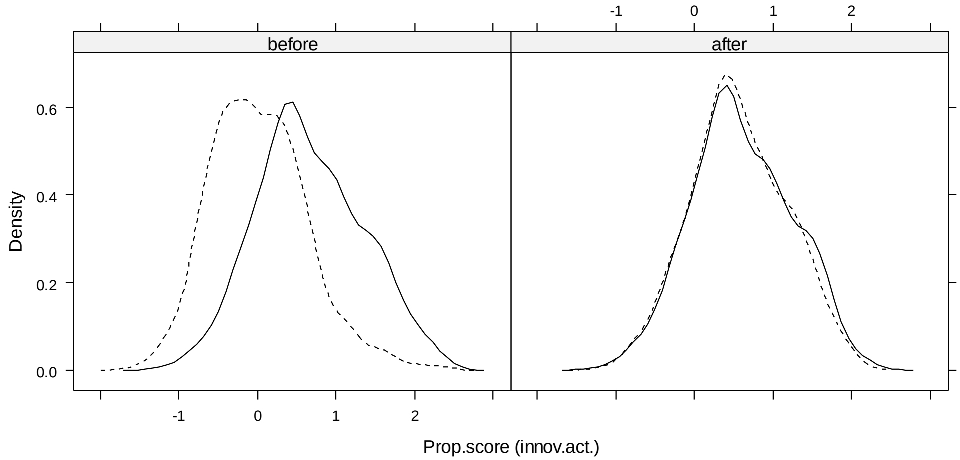

Figure 5-3. Distribution of the innovation activity propensity score.

To visually inspect the quality of our matching we display in the left panels of Figure 5-4 and Figure 5-5 the distribution of the propensity score for innovation activities, the distribution of the propensity score for public funding and the firm-size distribution for the sample of subsidized firms and the sample of non-subsidized firms before we employ the matching. In the right panel of the same figures we display the distribution for the sample of the subsidized firms and the matched sample of non-subsidized firms. The distributions are visualized by a kernel density plot, in which the sample of funded companies is represented by a solid line and the sample of non-funded firms is shown by a broken line. Establishing common support for the funded and non-funded firms leads to a loss of 1.9 percent of the treated observations.

In Figure 5-3 we observe, before we apply the matching, the difference in the distributions of the propensity score for innovation activities for the sample of funded firms (solid line) and the sample of non-funded firms (broken line). The distribution of the funded and the matched firms is rather similar after matching. As the propensity scores can be transformed into probabilities, the graphical representation supports the hypothesis that the matching algorithm succeeds in generating a control sample of non-subsidized firms with a probability distribution to carry out innovation activities, which is similar to the probability distribution of the funded firms.

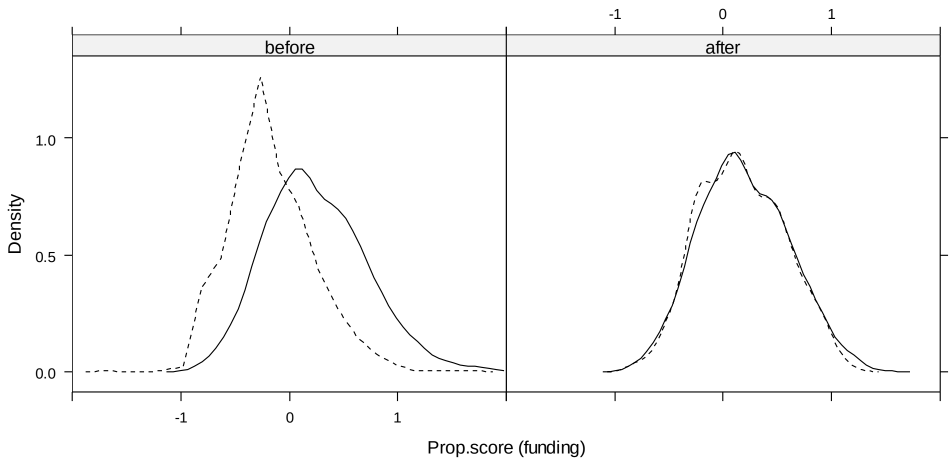

Figure 5-4. Distribution of the public funding propensity score.

Figure 5-4 displays an obvious difference in the distributions of the probability to receive public funding for funded and non-funded firms before the application of the matching. The probability to receive funding is computed based on company characteristics. It shows that the firms which actually received funding have a higher average likelihood to do so. They have firm-specific features which make them more likely to be selected for funding. However, the matched control group is comparable to the sample of funded firms, since the distribution to receive funding is quite comparable. Both samples now have a comparable distribution to receive public funding.

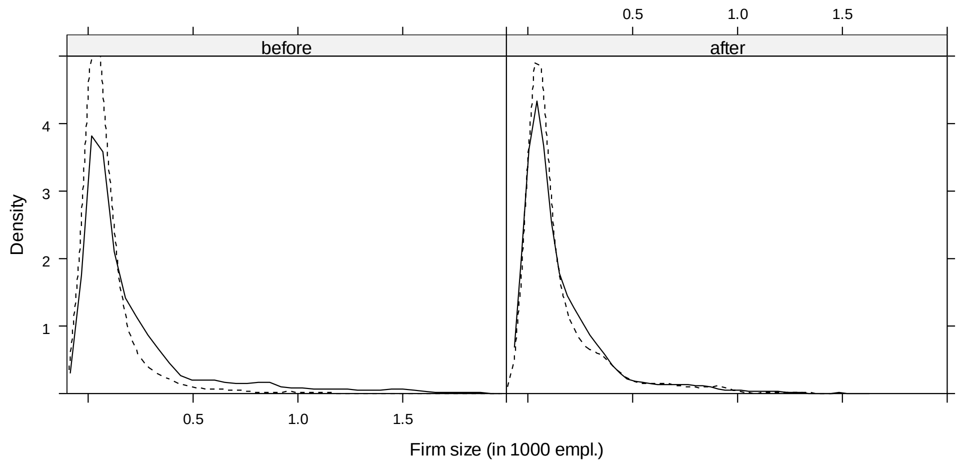

Figure 5-5. Distribution of firm size.

In figure Figure 5-5 the distributions of the public funding propensity scores differ before the matching. After the matching the distributions are similar.

Comparing the distributions of the variables used as matching criteria we come to the conclusion that the matching worked in the way it was supposed to. However, this does not necessarily mean that the comparable distributions of the propensity scores and the size translate into comparability based on the underlying firm characteristics which were used to generate the propensity scores. Table 5-21 compares the variable means of funded and non-funded firms. It reveals that, before matching, the means of the exogenous characteristics are significantly different for the funded and non-funded firms in the complete sample, as well as in the sample of the years 1996 and 2000, and in the sample of high technology manufacturing companies.

Table 5-21. Sample means before and after matching.

	Total		Year 1996		Year 2000		High Technology Man.	
	Fundzed	Non-funded	Funded	Non-funded	Funded	Non-funded	Funded	Non-funded
Before matching								
Employees	0.160	0.097 ***	0.194	0.106 ***	0.140	0.086 ***	0.158	0.106 ***
Employees (squared)	0.071	0.038 ***	0.096	0.046 ***	0.056	0.029 ***	0.064	0.040 ***
Share of R&D empl.	0.018	0.012 ***	0.016	0.012	0.019	0.011 *	0.015	0.005 ***
Share of R&D empl. (sq.)	0.003	0.003	0.003	0.003	0.003	0.002	0.002	0.000 ***
Prior patenting activity	0.363	0.127 ***	0.389	0.116 ***	0.348	0.140 ***	0.465	0.254 ***
Export as share of sales	0.388	0.225 ***	0.362	0.161 ***	0.403	0.300 ***	0.473	0.292 ***
Prop.score (funpub)	0.194	–0.174 ***	0.048	–0.332 ***	0.280	0.011 ***	0.415	0.133 ***
Prop.score (innov)	0.608	0.02 ***	0.365	–0.110 ***	0.750	0.173 ***	0.866	0.380 ***
Number of obs	620	1799	229	971	391	828	275	426
After matching								
Employees	0.160	0.151	0.194	0.185	0.140	0.131	0.158	0.151
Employees (squared)	0.071	0.066	0.096	0.092	0.056	0.050	0.064	0.062
Share of R&D empl.	0.018	0.015	0.016	0.017	0.019	0.014	0.015	0.017
Share of R&D empl. (sq.)	0.003	0.002	0.003	0.003	0.003	0.002	0.002	0.002
Prior patenting activity	0.363	0.310	0.389	0.333	0.348	0.296	0.465	0.457
Export as share of sales	0.388	0.384	0.362	0.328	0.403	0.417	0.473	0.509
Prop.score (funpub)	0.194	0.170	0.048	0.010	0.280	0.263	0.415	0.379
Prop.score (innov)	0.608	0.567	0.365	0.322	0.750	0.711	0.866	0.807
Number of obs.	620	620	229	229	391	391	275	275

Note: ***(**, *) indicates significance at the 0.1%,(1%, 5%) level of student’s t-test on equality of means.

In addition to the visual inspection of the quality of the matching and the comparison of the means of the exogenous company characteristics, we investigate whether the regression model already introduced in Table 5-18 can identify the publicly funded companies after the matching exercise. In the first column of Table 5-22 we report the regression of the public funding dummy on various exogenous characteristics of the firms. The upper part of the table contains the regressions before the matching, while the lower part reports the results of the regression after the matching. The left-most column displays the results for all observations. Before the matching the exogenous variables are significantly able to explain public funding. When the matched control group is in the sample – after the matching approach – the model loses explanatory power. It is no longer capable of explaining public funding at any reasonable level of significance. Note that the results in the first column of Table 5-22 differ from the results reported in Table 5-18, as in the former we use all observations, while in the latter we use only innovating companies. In all sub-samples that we analyze in Table 5-22, the models are able to explain public funding before matching. They cannot explain public funding after matching, lending further support to our hypothesis that the matching procedure is capable of generating comparable samples of funded and non-funded firms.

Table 5-22. Identifying funded companies before and after matching.

	Total	Year 1996	Year 2000	High Tech
Before				
Intercept	–1.901 ***	–2.300 ***	–1.651 ***	–1.508 ***
Employees	2.227 ***	2.484 ***	2.631 ***	2.303 **
Employees (squared)	–0.555	–0.794	–0.66	–0.893
Share of R&D employees	13.486 ***	14.857 **	12.663 ***	5.437
Share of R&D empl. (squared)	–38.685 ***	–44.323 *	–33.886 **	82.977
Prior patenting activity	0.835 ***	0.837 ***	0.825 ***	0.620 ***
Export as share of sales	1.108 ***	1.582 ***	1.108 ***	1.434
Chi2 (14)	433.09 ***	225.73 ***	192.35 ***	110.54 ***
After				
Intercept	–0.168	0.028	–0.226	0.208
Employees	0.274	0.675	0.816	1.340
Employees (squared)	–0.320	–0.799	–0.839	–1.120
Share of R&D employees	3.132	–0.620	4.587	–13.398
Share of R&D empl. (squared)	–3.592	–1.628	–0.170	47.860
Prior patenting activity	0.354 *	0.155	0.474**	0.085
Export as share of sales	0.014	0.348	–0.338	–0.571
Chi2(14)	11.23	10.49	21.98	7.56

Note: In the regressions in the first three columns the exogenous variables also contain nine industry dummies not reported here. ***(**, *) indicates significance at the 0.1%,(1%, 5%) level.

Given the discussion of the distribution of the matching variables, of the univariate analysis and of the multivariate analysis, we have good support for the matched sample of non-funded companies being a valid estimate of the counterfactual of the funded firms.

In Table 5-23 we display the impact funding has on the funded companies $E(\alpha_T)$. We report the average innovation intensity of the funded companies when they are funded $E(Y^T|d=1)$ and in the counterfactual case $E(Y^C|d=1)$ that they are not funded.

First of all, for the whole sample as well as for the sub-samples we analyze, we find a considerable and statistically significant impact of public funding on the innovation expenditure of the funded firms.

On average, the funded companies spend about 5.7 percent of their sales on innovation activities. Had they not been funded, they would have spent considerably less. The average treatment effect is about 3.6 percent of the companies' sales. The treatment effect is the same for the year 1996, the year 2000 and the sub-sample of the firms operating in high technology manufacturing sectors. Across the size classes the impact decreases with the size of the companies, although it still remains significantly positive.

In Table 5-24 we put the size of the impacts of public R&D funding in the context of the total innovation expenditure of the funded firms. For the average funded company, about 42 percent of its expenditure on innovation is unrelated to R&D funding. About 14 percent of the total expenditure of the average funded firm is contributed by the state through public subsidies. On average, the public contribution[28] to a funded project amounts to 44 percent of the total project costs (Tekes 2001). Hence, the subsidies have to be matched to another 18 percent of the overall innovation expenditure. 25 percent of the overall innovation expenditure of an average funded company is induced by the subsidies as additional innovation effort beyond the matching of the funding.

[28] We use the information of the National Technology Agency in Tekes (2001) as a proxy for the overall public contribution.

Table 5-23. Impact of public funding on innovation input.

	Total sample			Year 1996			Year 2000			High Tech Manufacturing		
	$E(Y^T \mid d=1)$	$E(Y^C \mid d=1)$	$E(\alpha_T)$	$E(Y^T \mid d=1)$	$E(Y^C \mid d=1)$	$E(\alpha_T)$	$E(Y^T \mid d=1)$	$E(Y^C \mid d=1)$	$E(\alpha_T)$	$E(Y^T \mid d=1)$	$E(Y^C \mid d=1)$	$E(\alpha_T)$
All	5.7%	2.1% ***	3.6%	5.4%	1.7% ***	3.7%	6.0%	2.3 ***	3.7%	6.2%	2.4% **	3.8%
Small (<=49)	7.1%	2.2% ***	4.9%	7.1%	1.7% *	5.4%	7.1%	2.5 ***	4.6%	8.1%	2.4% ***	5.7%
Medium (50–249)	4.8%	1.9% ***	2.9%	5.1%	1.6% ***	3.5%	4.6%	2.1 **	2.5%	5.0%	2.1% ***	2.9%
Large (>=250)	4.8%	2.2% **	2.6%	3.4%	2.0% **	1.4%	6.0%	2.5 *	3.5%	5.5%	2.9% *	2.6%
Numbers of obs.	620, 258, 234, 128			229, 78, 92, 59			391, 180, 142, 69			275, 101, 122, 52		

Note: Innovation input is measured by the innovation intensity computed by the innovation expenditure as a percentage of sales. *** (**, *) denote the significance of the t-test at the 0.1 percent, (1 percent, 5 percent) level.

Table 5-24. Estimated impact of public R&D funding in Finland.

	Total	Year 1996	Year 2000	Hi-Tech Man
Private financed innovation disbursements	43%	40%	44%	46%
Public R&D funding	14%	11%	17%	12%
Additional to match public funding*	18%	13%	22%	15%
Additional private innovation disbursements	25%	36%	17%	28%
Observed private total innovation disbursement	100%	100%	100%	100%

Note: * assumes 44 percent funding of project costs for simplicity. This intuitive presentation of the additionality is taken from Fier et al. (2004).

5.4.3 Matching with innovators

In this section we report the results for cases in which we construct the matched control group from the sample of all non-funded but innovating companies. This procedure implicitly assumes that innovation activity is independent of receiving funding for all the observed companies. Funding does not affect the R&D status of firms. As each company in the control group carries out innovation activities which require innovation input, the impact will be smaller than in the above case. The above case hence represents the upper boundary of the effect, whereas the analysis here will yield the lower boundary of the effect.

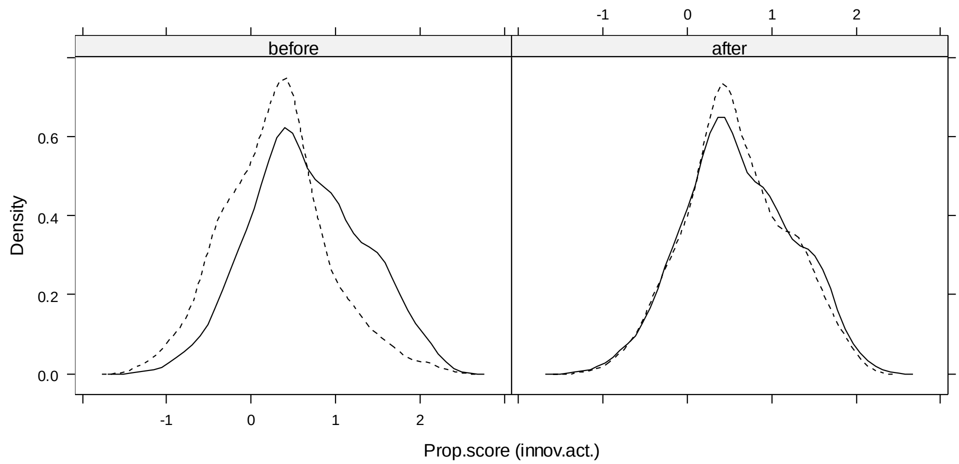

Figure 5-6. Distribution of the innovation activity propensity score.

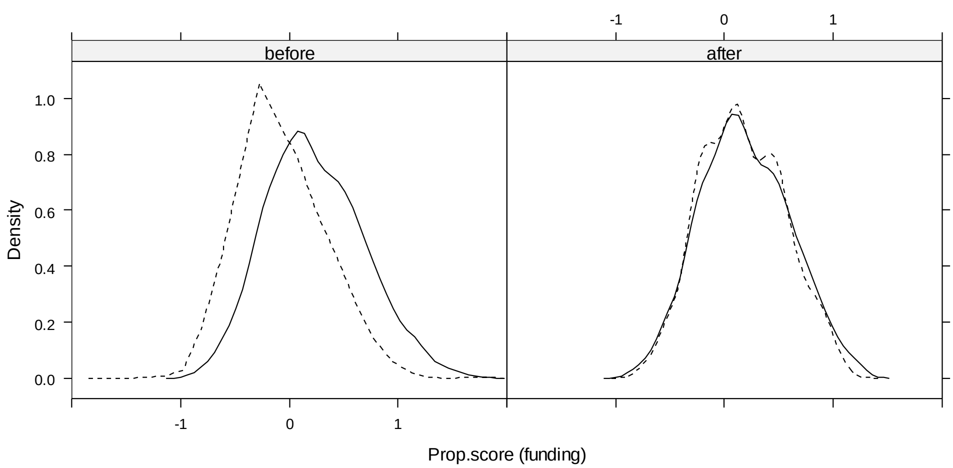

Figure 5-7. Distribution of the public funding propensity score.

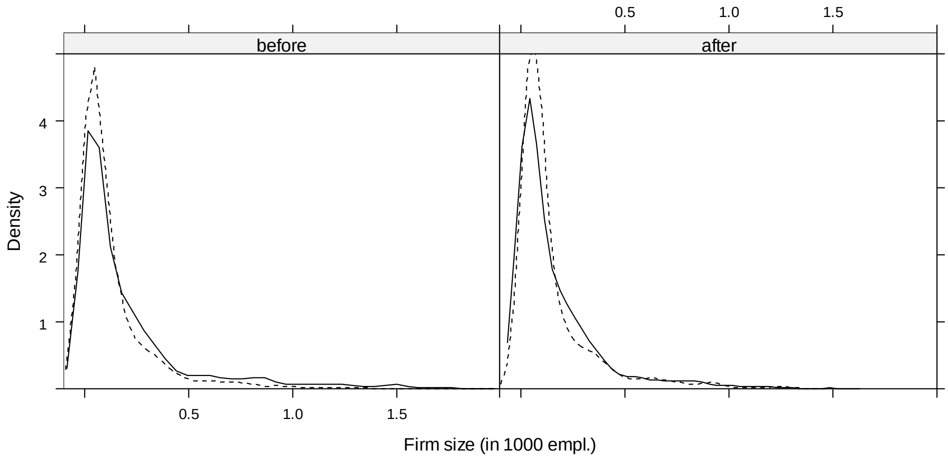

Figure 5-8. Distribution of firm size.

To inspect the success of the matching method in constructing comparable samples by controlling for the selection bias contained in the funding decision, we depict the distribution of an indicator of the propensity to carry out innovation activities, the distribution of the propensity to receive public funding and the distribution of the size of the companies. They are depicted in Figure 5-6, Figure 5-7 and Figure 5-8, where the solid line represents the sample of funded companies and the broken line the sample of non-funded but innovating companies before and after matching. Establishing common support required the deletion of 2.6 percent of the treated observations. We observe that the matching procedure is capable of creating a sample of non-funded companies that has an innovation probability distribution, a funding probability distribution and a size distribution that is similar to that of the funded companies.

Table 5-25. Sample means before and after matching.

	Total		Year 1996		Year 2000		High Technology Man.	
	Funded	Non-funded	Funded	Non-funded	Funded	Non-funded	Funded	Non-funded
Before matching								
Employees	0.160	0.132 ***	0.194	0.153 ***	0.140	0.111 **	0.158	0.142 *
Employees (squared)	0.071	0.061 ***	0.096	0.074 **	0.056	0.048 ***	0.064	0.048 **
Share of R&D empl.	0.018	0.016	0.016	0.019	0.019	0.014	0.015	0.006 **
Share of R&D empl. (sq.)	0.003	0.004	0.003	0.005	0.003	0.002 ***	0.002	0.000 **
Prior patenting activity	0.363	0.184 ***	0.389	0.189 ***	0.348	0.179 ***	0.465	0.320 ***
Export as share of sales	0.388	0.268 ***	0.362	0.234 ***	0.403	0.302 ***	0.473	0.365 ***
Prop.score (funpub)	0.194	–0.081 ***	0.048	–0.220 ***	0.28	0.054 ***	0.415	0.222 ***
Prop.score (innov)	0.608	0.283 ***	0.365	0.100 ***	0.75	0.461 ***	0.866	0.644 ***
Number of obs	620	706	229	349	391	357	275	197
After matching								
Employees	0.160	0.152	0.194	0.187	0.140	0.132	0.158	0.155
Employees (squared)	0.071	0.066	0.096	0.092	0.056	0.050	0.064	0.063
Share of R&D empl.	0.018	0.018	0.016	0.021	0.019	0.016	0.015	0.019
Share of R&D empl. (sq.)	0.003	0.003	0.003	0.004	0.003	0.002	0.002	0.003
Prior patenting activity	0.363	0.319	0.389	0.322	0.348	0.317	0.465	0.465
Export as share of sales	0.388	0.373	0.362	0.339	0.403	0.393	0.473	0.495
Prop.score (funpub)	0.194	0.168	0.048	0.012	0.28	0.258	0.415	0.371
Prop.score (innov)	0.608	0.575	0.365	0.326	0.75	0.719	0.866	0.809
Number of obs.	620	620	229	229	391	391	275	275

Note: ***(**, *) indicates significance at the 0.1%,(1%, 5%) level of student's t-test on equality of means.

Table 5-25 compares the sample means of the company characteristics of the funded and non-funded companies. It shows that, before matching, the sample means are significantly different for most of the characteristics. However, equality of the sample means cannot be rejected at the 5 percent level after matching.

In Table 5-25 we also report the mean propensity scores. Before the matching procedure the samples of the funded and non-funded companies have significantly different mean propensities to innovate and receive funding. After the matching procedure the equality of the means cannot be rejected.

Table 5-26. Identifying funded companies before and after matching.

	Total	Year 1996	Year 2000	High Tech
Before				
Intercept	–0.892 ***	–1.259 ***	–0.718 **	–0.229
Employees	0.576	0.384	1.323	–1.638
Employees (squared)	0.255	0.447	–0.200	2.915
Share of R&D employees	10.039 **	11.291 *	9.134 *	–20.720
Share of R&D empl. (squared)	–29.119 *	–34.529	–23.224	516.250
Prior patenting activity	0.634 ***	0.697 *^*	0.609 **	0.508 *
Export as share of sales	1.069 ***	0.914 **	1.014 ***	1.094 ***
Chi2	152.84 ***	74.93 ***	84.17 ***	41.07 ***
Df	14	14	14	6
After				
Intercept	–0.021	–0.059	–0.030	0.319
Employees	0.138	0.547	0.472	0.765
Employees (squared)	–0.115	–0.553	–0.363	–0.483
Share of R&D employees	–3.084	–8.105	–0.955	–25.094 *
Share of R&D empl. (squared)	12.074	19.549	12.924	83.824 *
Prior patenting activity	0.25884	0.254	0.248	–0.035
Export as share of sales	0.19366	0.092	0.248	–0.372
Chi2(14)	6.29	12.17	15.97	12.24
Df	14	14	14	6

Note: In the regressions in the first three columns the exogenous variables also contain nine industry dummies not reported here. ***(**, *) indicates significance at the 0.1%,(1%, 5%) level.

As in the discussion above, the quality of the matching is documented not only in terms of the visual representation of the distributions and the univariate analysis, but also by a multivariate analysis in which we examine whether exogenous company characteristics can explain funding in the samples before and after matching. Table 5-26 reports the results of regressing the public funding variable on the exogenous variables. For all sub-samples in the analysis before the matching procedure the exogenous company characteristics can jointly explain public funding. After the matching procedure the joint explanatory power vanishes.[29]

The above evidence on the quality of the matching process suggests that the matching procedure succeeded in generating a sample of non-funded firms which is comparable to the sample of funded firms and represents a valid estimation of the funded companies' counterfactual situation.

The assessment of the impact of public funding on the innovation input of funded companies compares the innovation input of the funded companies with their innovation input in the case that they had not been funded. In Table 5-27 we compare the means of the innovation input relative to companies' sales. For all observed sub-samples – the sub-sample of the year 1996, the sub-sample of the year 2000 and the sample of companies from high technology manufacturing – we observe a significantly positive impact if we pool all size classes. The estimated effect is around 2.5 percent of sales for all sub-samples except the high technology manufacturing firms. There the estimated effect amounts to 3.8 percent of sales.

For the pooled sample of all companies we observe that, with SMEs of fewer than 50 employees, public funding yields an effect that is as high as 3.4 percent. The effect decreases with increasing size of the companies to about 2 percent for larger SMEs and large companies. When we break down the sample into sub-samples based on the years of observation, the effects lose significance at the 5 percent level. However, some of the effects are significant at the 10 percent level. In all subsamples we observe the tendency that the effects with smaller companies is larger than with larger companies; not so in the subsample of the year 2000, though.

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[29] It must be mentioned that, within the sample of high technology manufacturing, the exogenous variables do not explain public funding at the 5% level of significance. However, they do at the 10% level of significance.

Table 5-27. Impact of public funding on innovation input.

		Total sample			Year 1996			Year 2000			High Tech Manufacturing		
		$E(\rho_1 \mid F=1)$	$E(\rho_0 \mid F=1)$	$E(\Delta_1)$	$E(\rho_1 \mid F=1)$	$E(\rho_0 \mid F=1)$	$E(\Delta_1)$	$E(\rho_1 \mid F=1)$	$E(\rho_0 \mid F=1)$	$E(\Delta_1)$	$E(\rho_1 \mid F=1)$	$E(\rho_0 \mid F=1)$	$E(\Delta_1)$
All		5.7%	3.3% ***	2.4%	5.4%	2.8% **	2.6%	6.0%	3.6% *	2.4%	6.2%	3.5% **	3.8%
Small	(<=49)	7.1%	3.9% *	3.2%	7.1%	3.5%	3.6%	7.1%	4.1% .	3.0%	8.1%	4.1% .	5.7%
Medium	(50–249)	4.8%	3.0% *	1.8%	5.1%	2.6% *	2.5%	4.6%	3.4%	1.2%	5.0%	3.1% ***	2.9%
Large	(>=250)	4.8%	2.7% *	2.1%	3.4%	2.3% *	1.1%	6.0%	3.0% .	3.0%	5.5%	3.5% .	2.6%
Numbers of obs.		620, 258, 234, 128			229, 78, 92, 59			391, 180, 142, 69			275, 101, 122, 52		

Note: Innovation input is measured by the innovation intensity computed by the innovation expenditure as a percentage of sales. *** (**, *,.) denote the significance of the t-test at the 0.1 percent, (1 percent, 5 percent,10 percent) level.

Table 5-28 estimates the decomposition of the impact of public funding on the innovation input of funded companies. For the whole sample the total innovation expenditure of the funded companies represents 100 percent – close to 60 percent of which would have been spent even in the case of not receiving funding. 15 percent of the total expenditure on innovation activities is in the form of public subsidies. Under the assumption of 44 percent cost sharing, this 15 percent must be matched by the appropriate amount of private expenditure, i.e. 18 percent of the total expenditure of the average funded firm. This is the private contribution to funded projects. The remaining 10 percent of the total expenditure for innovation is in addition to funding and private funds to match the grants. For the year 1996 we estimate this rate of additionality to be 26 percent of total company outlays on innovation. In the year 2000 the additional effect vanishes. This result is not particularly disturbing as the effect computed here is its lower boundary, while its upper boundary in the year 2000 is 17 percent of the companies' total outlay for innovation. The vanishing additional effect does not indicate that public funding substitutes for private efforts, as the matching funds by the company are still induced by the public funding. Moreover, the size of the additional effect also depends on the percentage of project costs covered by public funding. A discussion of this relationship can be found below in section 5.4.4. For high technology manufacturing firms this rate of additionality is 17 percent.

Table 5-28. Estimated impact of public R&D funding in Finland.

	Total	Year 1996	Year 2000	Hi-Tech Man
Private financed innovation disbursements	58%	52%	61%	59%
Public R&D funding	14%	11%	17%	12%
Additional to match public funding*	18%	13%	22%	15%
Additional private innovation disbursements	10%	24%	0%	14%
Observed private total R&D disbursement	100%	100%	100%	100%

Note: * assumes 44 percent funding of project costs.

5.4.4 Summary

In section 5.4.2 we investigate the impact of public funding on the funded companies, under the assumption that public funding has an influence on the decision whether or not to carry out innovation activities. In the previous section, section 5.4.3, we analyze the additionality under the assumption that the decision on whether to carry out innovation activities is taken prior to and independent of receiving funding. The first analysis suggests that the counterfactual can be constructed from non-funded firms regardless of their innovation behavior. Thus, non-funded firms without innovation activities at all can be included in constructing the counterfactual situation of a funded firm. Naturally, this reduces the overall innovation expenditure in the counterfactual situation and biases the estimation of the effect upward. The estimated effects are the upper boundary of the actual effect.

The second line of reasoning supports the idea that the counterfactual situation can only validly be constructed from non-funded but innovating firms. Firms used for the construction of the counterfactual situation of a funded firm tend to have positive innovation efforts. This results in higher innovation expenditure in the counterfactual situation as compared to the first setup of the analysis. This approach biases the innovation expenditure in the counterfactual situation upward. The estimated effects of funding in this situation are biased downwards.

Both types of analysis obviously bias the estimation of the effect of public funding. As such they represent an estimation of the upper and lower boundary of the real effects. They are reported in Table 5-29.

Table 5-29. Upper and lower boundary of the impact.

	Lower boundary	Upper boundary
Private financed innovation disbursements	58%	43%
Public R&D funding	14%	14%
Additional disb. to match public funding	18%	18%
Additional private innovation disbursements	10%	25%
Observed private total R&D disbursement	100%	100%

Note: The lower boundary is taken from Table 5-28 above. The upper boundary is taken from Table 5-24 above.

The first observation is that, although still positive, the lower boundary does not paint such a bright picture of the funding success as the upper boundary does. The impact varies between 10 percent and 25 percent of the total innovation expenditure. In addition, the estimated effect crucially hinges on the cost sharing scheme assumed. Until now, we assumed that 44 percent of the total project costs would be covered by the subsidy on average. Figure 5-9 contains a graphical representation of how the upper and lower boundaries of the additionality effect depend on the underlying cost-sharing rule.

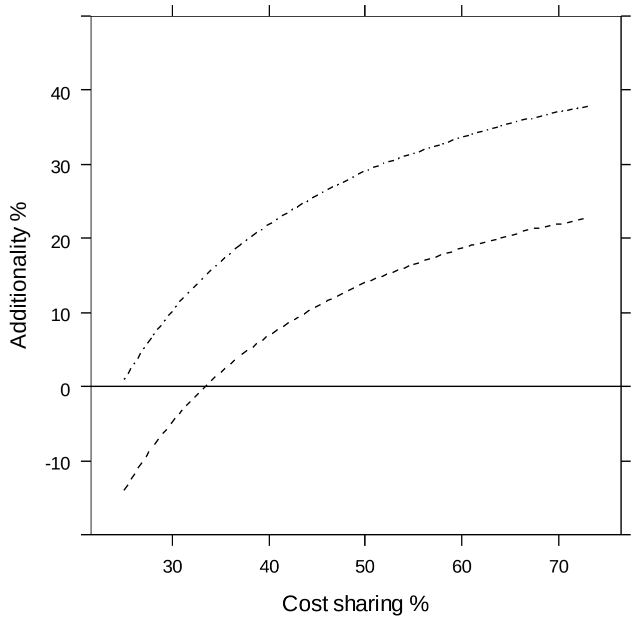

Figure 5-9. Upper and lower boundary of the additionality effect.

The horizontal axis of Figure 5-9 displays the cost-sharing percentage; for example, 35 percent indicates that 35 percent of the project costs are covered by public subsidies. The vertical axis reflects the additionality effect from row 4 of Table 5-29. The dashed line represents the lower boundary of the additionality effect, whereas the dashed dotted line represents the upper boundary.

Although there is no linear relationship between the cost-sharing scheme and the induced additionality, the relationship is monotonous. Figure 5-9 also illustrates the findings discussed above. At a cost-sharing scheme of 44 percent, the lower boundary of the effect is approximately 10 percent and the upper boundary is about 25 percent. Below a public coverage of approx. 38 percent of the project costs, there will be no additional effect of public funding in the case of the lower boundary. Even in this case, the additional disbursement to match the funding is positive. There is no crowding out of private innovation expenditure. The results provide evidence for a complementary relationship between public funding and private innovation expenditure.

As discussed above, the nominal effects on net innovation effort,[30] which we observe here, only translate into real effects on innovation effort if the nominal net increase in innovation expenditure is not offset by the wage increases of R&D staff. Georghiou et al. (2003) argue that the good performance of the Finnish innovation system is due to the constant increase in the number of science and engineering graduates. We can assume that the constant increase in labor supply sets clear limitations on the bargaining power of R&D employees. Hence, we can reasonably assume that the nominal net effects also translate into an increase in real R&D effort.

5.5 Comparison with results from German data

For the German data, a number of studies exist analyzing the input additionality of public R&D funding (Czarnitzki 2001, Czarnitzki 2002, Czarnitzki and Fier 2001, 2002 and Fier et al. 2004). These studies are comparable to the results presented above, as they all use data from the Community Innovation Surveys supplemented with data from other sources such as the patent office and other firm-specific data from the CreditReform company data base. In general the analysis is based on the same core data used in the Finnish context presented above. In addition, as discussed above, governmental intervention in Finland and Germany is based on a comparable set of measures – the focus being on direct project funding and an absence of tax incentives for R&D.

Generally, the studies find strong evidence for input additionality for the German funding. Czarnitzki and Fier (2001, 2002) use a matching approach and find that public funding does not fully crowd out private investment in R&D. Their analysis is limited in the sense that the data only contains a dummy variable for public funding. The size of the subsidy is unknown and partial crowding out cannot be rejected. In his selection models, Czarnitzki (2002) finds strong evidence for positive effects of public funding on the R&D intensity of German firms, although the effect among Eastern German firms is higher than among Western German firms.

[30] See page 33 above.

Table 5-30. Comparing the results.

	Lower bound. (FI)	Upper bound. (FI)		FHH (DE)
Private financed R&D disbursements	58%	42%		57%
Public R&D funding	14%	14%		16%
Additional to match public funding*	18%	18%		16%
Additional private R&D disbursements	10%	25%		11%
Observed private total R&D disbursement	100%	100%		100%

Note: The lower boundary is taken from Table 5-28 above. The upper boundary is taken from Table 5-24 above. FHH refers to Fier et al. (2004).

Fier et al. (2004) analyze the input additionality of R&D subsidies for the broad field of production technology – with the sample of funded firms being a sub-sample of the total population of funded firms. The field of production technology encompasses a broad set of targets and a variety of different types of funded projects, such as projects to improve production processes as well as projects to launch new products especially in the machinery and tool industry.

To compare the results obtained by Fier et al. (2004; see Table 5-30), we approximate the composition of their sample by analyzing only a sub-sample of the firms in the analysis above. Then we use the appropriate industrial sectors[31] and all process innovating companies. For the sub-sample we compute the upper and lower boundaries of the effect. Although Fier et al. (2004) delineate their sample of funded firms by the funding program, we delineate the sub-sample here on the basis of the industrial sector and the type of innovation activity of the firm. However, as we have seen for the whole sample above, the additionality effects in the German analysis are between the lower and upper boundaries of the Finnish results. Table 5-31 summarizes the results for the sub-sample of firms which can be broadly associated with production technology.

[31] The relevant industrial sectors are summarized in row 5 and row 6 in Table in Appendix B.

Table 5-31. Comparing the results for a sub-sample of firms.

	Lower bound. (FI)	Upper bound. (FI)		FHH (DE)
Private financed R&D disbursements	62%	47%		57%
Public R&D funding	14%	14%		16%
Additional to match public funding*	19%	19%		16%
Additional private R&D disbursements	5%	20%		11%
Observed private total R&D disbursement	100%	100%		100%

Note: The sub-sample of firms analyzed here is broadly associated with production technology. FHH refers to Fier et al. (2004).

Comparing the results for Fier et al. (2004) with the observed results in the Finnish sub-sample which we broadly associated with production technology, we find that the input additionality effects in the German sample are between the lower and upper boundaries of the Finnish results. Yet, given the different delineation of the analyzed firms, the magnitude of the actual effects can be said to be comparable.

In section 5.6 we present a comparable analysis using selection models to examine how robust the results of the matching analysis are. In particular, we investigate whether the restriction of the matching analysis (so that it only controls for selection on observables) matters for the result of the analysis.

5.6 Input additionality – selection models

The econometric analysis using selection models to estimate the impact of R&D funding essentially differs from the matching approach in the sense that selection models require the estimation of both the funding equation and the estimation of the equation determining the innovation effort (innovation expenditure) of the firm.[32] Additionally, selection models, as we will employ them below, require the assumption of a functional form of the relationships. In contrast, the matching approach does not require a functional form. Similar to the matching

[32] See section 4.3.4 on page 87 above.

approach, the selection model takes account of the fact that receiving public funding is not a random event. Certain firm- and industry-level characteristics influence the likelihood of a company receiving public funding. They are estimated in the selection equation. The results of the selection equation are incorporated in the equation determining the innovation expenditure to control for the selection bias. In accordance with Heckman (1979), we include the Mills Ratio (*millsF*) for funded companies and the Mills Ratio (*millsN*) for non-funded companies in the estimation of R&D expenditure.

We use only the sample of innovating companies. Hence, we refer to the case in which funding decisions have no influence on R&D status and only influence the intensity of carrying out R&D. (See Tables 5-32 and 5-33.)

Table 5-32. Estimation of the funding probability.

	Estimate	Std.error
Intercept	–1.188 ***	0.195
Employees	1.090 .	0.567
Employees (squared)	0.007	0.397
Share of R&D employees	10.321 **	3.663
Share of R&D empl. (squared)	–29.317 *	12.976
Prior patenting activity	0.648 ***	0.141
Export as share of sales	0.970 ***	0.214
Part of a corporate group	–0.141	0.131

Note: ***(**, *, .) indicates significance at the 0.1%,(1%, 5%, 10%) level.

Table 5-33. Estimation of the R&D effort.

	Estimate	Std.error
(Intercept)	–224.2	289.9
Mills Ratio millsF	–2334.0 ***	579.3
Mills Ratio millsN	–1694.9 **	563.7
Public funding	3802.4 ***	933.1
Employees	4981.5 ***	710.3
Employees (squared)	–1759.7 ***	401.6
Prior patenting activity	–767.6 **	266.5
Export as share of sales	–829.2 *	383.0
Hampering factors	77.8	204.8
Part of a corporate group	197.3	152.9

Note: ***(**, *) indicates significance at the 0.1%,(1%, 5%) level.

Both the matching approach and the selection models have their advantages. As discussed above, the matching approach does not require a specified functional form for the estimation of the treatment effect. The selection models do, however. On the other hand, the matching approach has the disadvantage of correcting only for selection on observables. The selection models do not have this restriction. As Table 5-34 illustrates, the matching approach and the selection model essentially yield additionality effects of comparable size. This suggests that the limitation of the matching approach to only correct for selection on observables does not lead to strong biases in the results.

Table 5-34. Results of the matching approach and the selection model.

	Matching	Selection model[1]	Selection model[2]
Private financed R&D disbursements	58%	62%	59%
Public R&D funding	14%	14%	14%
Additional to match public funding*	18%	18%	18%
Additional private R&D disbursements	10%	6%	9%
Observed private total R&D disbursement	100%	100%	1005

Note: The lower boundary is taken from Table 5-28 above. [1] All companies in the sample. [2] Only companies which can be broadly associated with production technology in the sample – for comparability with Fier et al. (2004).

In addition, comparing the restricted sample of firms broadly related to production technology yields comparable results to those in Fier et al. (2004). Hence, we have no indication that the matching analysis above is burdened by the restriction that matching only controls for selection on observables.

5.7 Summary

The analyses in this section show that public subsidies induce Finnish firms to spend more on innovation than they would without the subsidies. Public funding exhibits a strong input additionality effect. The results of the analyses above not only exclude complete or partial crowding out, but also suggest complementarity of public funding and private R&D expenditure. The results are in line with the findings for a comparable set of German companies. The lower boundary of the size of the effect is of the same magnitude as the effect in the analysis of the German sample.

The results obtained here are also in accordance with the findings of Almus and Czarnitzki (2003), Busom (2000), Czarnitzki (2001), Czarnitzki and Fier (2001, 2002), Czarnitzki and Hussinger (2004), Duguet (2003), Gonzales et al. (2004), Hussinger (2003), Licht and Stadler (2003). However they are contradictory to the results of Wallsten (2000) for the US. Moreover, our results are somewhat contradictory to the findings of Toivanen and Niininen (2000) for a sample of

Finnish companies. Yet, on average, our results are compatible with the findings in Ali-Yrkkö (2005) for a panel of Finnish firms.

The details vary, though. Ali-Yrkkö (2005) finds that the additionality increases with the size of the firm. However, our results suggest that the effects decrease with size.[33] If additionality effects decrease with size, small and medium sized companies tend to enjoy relatively larger effects than larger companies do, which would eventually lead to a less unequal distribution of R&D activity in companies. Czarnitzki and Ebersberger (2005) find support for the fact that R&D subsidies in both Finland and Germany reduce inequality in the distribution of R&D activities.[34] In addition, Czarnitzki and Ebersberger (2005) find a positive effect of subsidies on the mean number of R&D personnel employed by the funded firms. This finding suggests that the nominal effect that we find in the analysis above is not – or at least not completely – offset by increasing the wages of R&D employees. In fact the increased innovation expenditure translates into higher real innovation effort.

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[33] The differences between the detailed results obtained by Ali-Yrkkö (2005) and the results obtained here may be due to a variety of factors, such as data coverage in terms of sector and detail. Ali-Yrkkö uses data covering only one industry, whereas the analysis presented here covers all manufacturing sectors and knowledge-intensive service sectors. Our public subsidy variable is only dichotomous, whereas Ali-Yrkkö uses a continuous variable indicating the size of the funding. Differences in the econometric setup and the temporal data coverage may also add to the differences.

[34] Czarnitzki and Ebersberger (2005) compute various inequality indices for the distribution of R&D employees across firms. An actual scenario with R&D subsidies distributed among some of the firms is compared to the counterfactual scenario where no R&D subsidies are distributed. Both in Finland and in Germany the presence of subsidies reduces the unevenness of the distribution of the R&D effort within the population of companies.

6. Output additionality

_______ *This section investigates the impact of public funding and collaboration on the innovation output of companies. The particular setup of the analysis assesses the mean effect of actual policies. Additionally, it can also highlight the mean effects of potential policy changes and policy options. The analysis includes an identical analysis for a sample of German firms which facilitates close comparison of the results.* ___________________________________

6.1 Introduction

In this section we consider the impact of public funding and collaboration on innovation output. We basically focus on the output additionality effects of public funding. As the funding rules of the major financing agency in the Finnish innovation system suggest that collaborative R&D is preferred in funding decisions, companies have an incentive to collaborate in projects for which they seek public funding. In the context of sharing knowledge and sharing costs, collaboration makes sense from the social point of view. However, there are not only social benefits from R&D collaboration, but also private benefits for the collaborating firm itself. Hence, collaboration is not just a phenomenon among publicly funded firms. It also occurs independently of public subsidies. Therefore, the effects of public funding and collaboration have to be disentangled.

The main target of this section is to separate the effects of public subsidies from the effects of collaboration on the companies' output from R&D. The analysis in this section is largely based on Czarnitzki et al. (2004c). But the discussion offered here goes somewhat beyond.

6.2 Output additionality and the matching approach

Our particular focus is the output additionality of public funding, i.e. how collaboration for innovation and public funding affects the innovation output. In line with the discussion in section 2.4.2.2.1, we use the probability to patent as an indicator of innovation output. Our results can be interpreted in terms of innovative output in general. In the following discussion we use patenting and innovative output and outcome synonymously.

6.2.1 Research design and econometric methodology

As collaboration and funding are neither mutually exclusive nor congruent, we distinguish four groups of innovating companies:

(1) firms that neither participate in any collaborative innovation network nor receive public R&D funding

(2) firms that do not receive public R&D funding but are involved in cooperative R&D

(3) firms that receive public funding but are not engaged in collaborative R&D

(4) firms that 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 higher innovation productivity, resulting in increased patenting activities due to positive knowledge spillover effects.

The methodology used here is a variant of the matching approach discussed in 4.3.5. However, as discussed above, we do not have only a sample of funded companies and a sample of non-funded companies from which to construct the treatment and the control group. Essentially, we have four different groups of companies, which requires some elaboration on the methodology employed. In the subsequent analysis we consider the receipt of public subsidies and the engagement in collaboration as heterogeneous treatments, in order to disentangle the effects due to collaboration from those due to public funding. Suppose there are M different states of treatment and the receipt of one particular treatment m is indicated by the variable $d \in \{0, 1, \ldots, M\}$. The average treatment effect of the firms receiving m relative to l can be written as

$$E(\alpha^{m,l}) = E(Y^m \mid d=m) - E(Y^l \mid d=m) \qquad (19)$$

where Y^m and Y^l denote the outcome in the different states. Derived from the groups of firms above, the different treatment states can take four different M values:

(1) none

(2) publicly funded

(3) collaboration

(4) both publicly funded *and* collaboration.

Given our possible combinations of public funding and collaboration, we can distinguish all cases of the treatment effect that are summarized in Table 6-1. Both columns and rows contain the treatment states. The columns contain the actual treatment states and the rows contain the counterfactual treatments. It reads from column to row, for example:

> Case 1: Given that the firms collaborate but are not subsidized, what is the difference between the actual innovation output and their innovative output if they had not collaborated?
>
> Case 4: For firms which neither collaborate nor receive subsidies, what is the difference between their actual innovative output and their innovation output in the case that they had collaborated (and not received public funding)?

Table 6-1. Research questions.

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

As we discussed above, each case requires the estimation of a counterfactual situation, since, 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 the receipt of funding and collaboration are subject to a potential selection bias. Concerning the funding, companies themselves choose to apply for, 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 non-funded ones, just as the group of collaborating companies is different from the group of non-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.

To analyze the impact of collaboration and public funding, we employ the matching approach introduced in section 4.3.5. 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 programs which we are using here. As we have seen, 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*.

Following Gerfin and Lechner (2002), the treatment effect can be calculated by

$$E(\alpha^{m,l}) = E(Y^m \mid d = m) - E(Y^l \mid d = m) = \quad (20)$$

$$= E(Y^m \mid d = m) - E_{P^m(X),P^l(X)}\{E[Y^l \mid P^m(X), P^l(X), d = l] \mid S = m\} \quad (21)$$

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 6-2 and follows Gerfin and Lechner (2002). As the propensity score is not known, it has to be estimated. We specify a bivariate probit model regressing both public funding and collaboration for innovation on a set of exogenous variables. The propensity scores of these regressions express the propensity to enter collaboration and/or to receive public funding. One difference of our application from the matching conducted by Gerfin and Lechner (2002) 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. 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 6-2. Matching protocol.

Step 1	Specify and estimate a bivariate probit model to obtain the propensity scores.	
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 observation 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-statistic is biased, because it does not take the appearance of repeated observations into account. Therefore, we have to correct the standard errors in order to draw conclusions on statistical inference. We follow Lechner (2001) and calculate his estimator for an asymptotic approximation of the standard errors.	

6.2.2 Data source, variables and descriptive statistics

As discussed above in section 4.2, the common data source for the whole of this research is the Community Innovation Survey. For this section the data has been complemented by data taken from patent statistics. With regard to the German data, we use only Western German companies rather than all German companies, since Western German firms are more comparable with Finnish companies, whereas Eastern German firms are still affected by the transformation from a planned economy to a market economy and may not, therefore, 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, which means that these firms introduced either 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 those in Germany, on average. In order to have more comparable samples, we exclude the largest firms from both samples and drop the firms with fewer than ten employees from the German data. Hence both samples cover firms from ten employees up to firms with 2,500 employees.

As we are investigating the innovation output, we restrict our sample to firms performing innovation activities. Recalling the arguments presented in the sections above, we therefore assume that the granting of funds for R&D does not change the R&D status of the firm. Firms' decisions to carry out innovation activities do not depend on positive decisions to receive grants. As a consequence, the effects we observe are the lower boundary of the real effects. Including all companies regardless of their innovation activities would certainly bias the findings upwards.

The German and Finnish samples and the variables used in the analysis below are characterized in Table 6-4 and Table 6-5. As described above, the treatments are indicated by two dummy variables: one indicating firms engaged in collaborative research projects and the other denoting publicly funded firms. The collaboration variable 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. Neither does our collaboration indicator specify any particular collaboration partner. It indicates collaboration for innovation with any of the following types of partners: (1) Customers or clients, (2) Suppliers, (3) Competitors, (4) Universities, (5) Private research labs, (6) Governmental or non-profit research organizations, (7) Consulting firms.

The share of firms performing collaborative research is about 29 percent in Germany but 64 percent in Finland. In the Finnish (German) sample about 48 percent (21 percent) of all firms receive R&D subsidies. The share of firms receiving subsidies *and* engaging in collaboration simultaneously is 11 percent in Germany and 39 percent in Finland. This huge difference impressively reflects the Finnish policy efforts to foster innovation by inducing collaborative R&D. (See Tables 6-3 and 6-4.)

Table 6-3. Descriptive statistics of the Finnish sample (N = 1,520).

Definition	Mean	Std. dev.	Min.	Max.
Patent application (dummy)	0.259	0.437	0.000	1.000
Employees in 1,000s	0.182	0.214	0.010	2.025
Share of R&D employees	0.076	0.117	0.000	1.000
Patent stock (dummy)	0.275	0.433	0.000	1.000
Export as share of sales	0.342	0.314	0.000	1.000
Public funding (dummy)	0.483	0.500	0.000	1.000
Cooperation (dummy)	0.643	0.479	0.000	1.000
Public fund. & Coop. (dummy)	0.386	0.487	0.000	1.000
Year 2000 (dummy) –	0.602	0.490	0.000	1.000

Note: The sample is restricted to innovating companies. The analysis includes nine industry dummies not reported here.

Table 6-4. Descriptive statistics of the German sample (N = 1,464).

Definition	Mean	Std. dev.	Min.	Max.
Patent application (dummy)	0.438	0.496	0.000	1.000
Size in 1,000 employees	0.312	0.401	0.010	2.500
Share of R&D employees	0.087	0.187	0.000	1.000
Patent stock (dummy)	0.439	0.496	0.000	1.000
Export as share of sales	0.242	0.239	0.000	1.000
Public funding (dummy)	0.208	0.406	0.000	1.000
Cooperation (dummy)	0.287	0.452	0.000	1.000
Public fund. & Coop. (dummy)	0.110	0.313	0.000	1.000
Year 2000 (dummy)	0.333	0.401	0.000	1.000
				.

Note: The sample is restricted to innovating companies. The analysis includes nine industry dummies not reported here.

We use other variables to control for firm heterogeneity, such as a log of firm size measured as the number of employees. Note that even the limitation whereby firms have a maximum of 2,500 employees 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. To describe historical technological experience, we control for past applications in the long run; i.e. the dummy takes a 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 by three years – e.g. in CIS III the question on collaboration covers 1998 to 2000, while the lagged previous patenting variable covers the years until 1997. The data is taken from the German and Finnish Patent Offices[35]. 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 the previous patenting variable as a control variable in the matching process. In addition to

[35] Data from the Finnish Patent Office is supplied by Statistics Finland.

previous patenting activities, the current potential to patent clearly depends on the firms' current R&D engagement. We measure this by R&D intensity in real terms, i.e. the number of R&D employees as a percentage of total employment, to reduce collinearity with firm size. Again, we find that R&D activity measured as R&D intensity is higher in Germany than in Finland, on average. Nine main sectors of economic activity are distinguished on the basis of the NACE classification.[36] They capture the differences between the business sectors. Finally, a time dummy reflects changes in patenting activities over time.

The variables indicating the previous experience, the size of the company and its R&D effort are important characteristics to be considered in the selection of companies to be funded, as governments may pursue a pick-the-winner strategy. This means that, in order to receive public funding, firms should show previous successful innovation results – indicated by patenting activity – and prove that they maintain the capacity and capabilities to conduct the proposed research projects successfully. An obvious indicator of capacity is firm size, while that for capabilities is the R&D effort, of course. These variables should be important not only for modeling the subsidy receipt, but also for the collaboration decision. On the one hand, firms can only benefit from spillovers if they maintain a critical mass of absorptive capacity (Cohen and Levinthal 1989). On the other hand, they must have something to offer (knowledge) to convince potential partners they would both benefit from cooperating. Both factors are captured by the lagged experience variable and the variable indicating R&D efforts. Admittedly, the R&D effort variable holds some possible danger of causing endogeneity, at least in the policy equation, if firms hired additional personnel due to past funding. Unfortunately, we cannot rule this problem out by using lagged values for R&D efforts, as this information is not available in the cross-sections of the CIS surveys and the discussion above shows that it is very important to include the R&D effort as a covariate. Note, however, that if some endogeneity does occur, we would underestimate the actual treatment effect on the treated, due to this shortcoming of the model. If we find positive effects, however, 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 modeled by Cassiman and Veugelers

[36] See Appendix B.

(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 indicating firm size, firms' R&D effort and their lagged patenting experience 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.

6.2.3 Estimation results

This section presents the estimation results. First we show that public funding and collaboration for innovation has a positive impact on the generation of innovation output in the raw unmatched data. The matching analysis then estimates, for each of the 12 treatment state – counterfactual combinations, the innovation output in the treatment group and their counterfactual output.

6.2.3.1 Probability to patent

As a first step, we consider collaboration for innovation and being funded as exogenous, and we regress the patent dummy on our explanatory variables, including an interaction term indicating funding and collaboration. As shown in Table 6-5 and Table 6-6, we first find that firms that have been funded exhibit a significantly higher probability to file a patent than non-funded firms both in Germany and in Finland. We also find a positive impact of the collaboration dummy on the propensity to patent in both countries. Collaboration and receiving funding simultaneously is insignificant. Patenting history has a strong positive influence on the propensity to patent. Further results in Table 6-5 and Table 6-6 reveal the expected effects of the control variables; larger firms are more likely to 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.

Besides the estimated coefficients, we also computed marginal effects of collaboration and public funding 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 percent level.

Table 6-5. Probit estimates of the patenting activity in the Finnish sample.

Patent	Coef.	Std.err.
Employees	0.214 ***	0.033
Share of R&D empl.	1.061 ***	0.297
Prior patenting activity	0.892 ***	0.085
Export as share of sales	0.406 ***	0.133
Public funding	0.365 ***	0.161
Cooperative R&D	0.486 ***	0.128
Funding and Cooperation	–0.025	0.188
Intercept	–1.574 ***	0.164
Log likelihood	–651.199	
McFadden R^2	0.282	

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

Table 6-6. Probit estimates of the patenting activity in the German sample.

Patent	Coef.	Std.err.
Employees	0.280 ***	0.035
Share of R&D empl.	0.762 ***	0.226
Prior patenting activity	0.936 ***	0.086
Export as share of sales	0.937 ***	0.181
Public funding	0.395 ***	0.135
Cooperative R&D	0.518 ***	0.104
Funding and Cooperation	–0.336	0.205
Intercept	–0.847 ***	0.127
Log likelihood	–655.322	
McFadden R^2	0.347	

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

At this stage we can conclude that both public funding and collaboration increase companies' propensity to yield innovation output. This supports our hypothesis that both funding and collaboration have a positive effect on the generation of innovative output. Yet, the probit regressions above do not fully account for the effect that the sub-sample of funded firms is different from the sub-sample of non-funded firms by selection. In the following section we use the matching procedure to tackle the selection bias and to estimate the effect of funding and collaboration.

6.2.3.2 Matching

We now address the problem of a selection bias and consider collaboration and funding as endogenous variables. As indicated above, we expect a high correlation between collaborative research and public funding, as research networks are among today's most important policy tool in both 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 bivariate probit model allowing for correlation among alternatives. The results are given in Table 6-7 and Table 6-8.

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 percentage of project-related funding in Finland, puts strong emphasis on the economic viability of the results of funded projects, special attention is paid to companies' competitiveness and the competitive advantage of the technology involved in the project (Tekes 2005a). In a small open economy, the latter in particular leads to an emphasis on export-oriented companies.

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

Table 6-7. Bivariate probit results for the Finnish sample.

	Coef.	Std.err.
Public funding		
Employees	0.167 ***	0.028
Share of R&D employees	2.198 ***	0.285
Prior patenting activity	0.394 ***	0.083
Export as share of sales	0.507 ***	0.119
Intercept	–0.423 ***	0.115
Cooperation		
Employees	0.276 ***	0.028
Share of R&D employees	1.851 **	0.308
Prior patenting activity	0.268 ***	0.088
Export as share of sales	0.292 **	0.124
Intercept	0.852	0.122
Disturbance correlation	0.423 ***	0. 040

Table 6-8. Bivariate probit results for the German sample.

	Coef.	Std.err.
Public funding		
Employees	0.112 ***	0.034
Share of R&D employees	1.087 ***	0.199
Prior patenting activity	0.325 ***	0.092
Export as share of sales	0.130	0.175
Intercept	–0.954 ***	0.125
Cooperation		
Employees	0.169 ***	0.032
Share of R&D employees	0.940 ***	0.193
Prior patenting activity	0.262 ***	0.085
Export as share of sales	0.459 ***	0.165
Intercept	–0.888 ***	0.122
Disturbance correlation	0.382 ***	0.046

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 6-7 and Table 6-8, including the following additional regressors: the interaction terms of firm size, R&D effort and the lagged patenting experience, 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 of the treated and the control group. Once the propensity scores are estimated, we drop the firms lacking common support. Table 6-9 and Table 6-10 present the impact of the common support restriction for each group considered in the following matching analysis. The lost observations amount to about 16 percent in the German sample and only 6 percent in the Finnish sample. 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 6-9. Initial Finnish sample; loss due to common support.

	Initial sample	Loss due to common support restriction
Firms that neither collaborate nor receive funding	394	4.8%
Collaborating firms	392	2.6%
Publicly funded firms	148	3.4%
Firms that receive subsidies and also collaborate	586	10.4%
Whole sample	1,520	6.3%

Table 6-10. Initial German sample; loss due to common support.

	Initial sample	Loss due to common support restriction
Firms that neither collaborate nor receive funding	901	21.5%
Collaborating firms	259	7.7%
Publicly funded firms	143	7.7%
Firms that receive subsidies and also collaborate	161	7.5%
Whole sample	1,464	16.2%

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 neighbors for each firm to be evaluated. Yet, for the computation of cases 8, 9 and 12 in the Finnish sample we had to drop observations below the 5 percent and above the 95 percent percentiles of the firm size distribution to get a successful matching result. In this case, and in case 7, we searched for only one control observation. Also in the cases 4, 7 and 10 in Germany we searched for only one nearest neighbor. Cases 4, 7 and 10 amount to the average effects on untreated firms. In a few cases we also included the R&D effort as an additional matching criterion in the calculation of the Mahalanobis distance.

6.2.4 Basic model for interpretation

As laid out in section 6.2.1, we explore all possible cases that can be constructed from our set of heterogeneous treatments. If we again explore the structure of Table 6-11 we observe that an analysis of the average effects of actual policy and an analysis of the potential policies is possible with the given setup.

For instance, given that the observed companies collaborated for innovation but did not receive funding, case 1 asks what the output of their innovation activity would have been if they had not collaborated? The numbers reported in the result tables below are the difference in the outcomes of the actual and counterfactual situations. The effect of the actual collaboration is analyzed in this case.

Case 2 compares the actual situation of funded (but non-collaborating) companies with the counterfactual situation of no funding. But in case 9 the actual situation of simultaneous collaboration and receipt of funding is compared to the counterfactual situation of public funding and no collaboration. The effect of actual collaboration on top of public funding is shown here.

For a contrary example, take case 7. The actual situation of companies that neither collaborate nor receive funding is compared to the counterfactual situation of being funded. The effect that we report in this case is the effect foregone on innovation output by not funding the companies that neither collaborate nor receive funding. At the same time, the magnitude given is the average effect one would expect, if funding were distributed to the non-funded (and non-collaborating) companies.

As a final illustrative example, take case 12. It compares the innovation outcome of the companies that are actually funded to the counterfactual situation of both funding and collaboration. In other words, case 12 reports the average potential effect that might be achieved by inducing funded companies to additionally collaborate for innovation.

Table 6-11. Analysis model – actual vs. potential policy.

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

To sum up, the setup enables us to analyze the effects of both *actual* policies and *potential* policies. The dark shaded cases in Table 6-11 analyze the actual policies and behavior. The white shaded cases in Table 6-11 show the effects of potential behavior or policies. Cases 5 and 8 are reported for completeness, here. Their implicit meaning of either collaboration or funding, and their comparison to states, does not relate to any intuitive real world political setting or funding principle.

Note that, although we have discussed actual policies above, it is not completely in accordance with the interpretations of cases 1, 3, 6 and 11. In these cases, collaboration without being funded is either the factual or the counterfactual situation. As no funding is involved here to induce collaboration, we can denote collaboration in these cases as voluntary.

6.2.5 Results of the Finnish sample

Table 6-12 reports the average treatment effects for the Finnish sample using the matching approach to construct the counterfactual situation. In the following sections we will first turn to a discussion of the effects of actual policy and then present the effects caused by potential changes or extensions in the overall policy.

Table 6-12. Matching results for Finland: average treatment effects.

		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	

Note: Standard errors in parentheses. *** (**,*) indicates a 1% (5%, 10%) significance level (two-sided test). Standard errors are obtained with Lechner's (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. For the computation of cases 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 for only one control observation.

The numbers given at the main diagonal of Table 6-12 give the innovative output of the average firm in the factual state *m* in terms of likelihood of applying for a patent. 9.3 percent of the companies that neither receive funding nor collaborate for innovation file for a patent. 22 percent of the collaborating companies and 20.3 percent of the funded companies do so. The strongest propensity to patent can be observed among those companies that both collaborate and receive funding. The other cells contain both the estimation of the effect (i.e. the average difference of the innovation output in the factual situation) and the innovation output in the counterfactual situation (also measured in the probability to patent). The standard errors are given in parenthesis. The asterisks indicate the level of significance.

6.2.5.1 Actual policy

This section discusses the effects yielded by actual policy and actual behavior yield on the basis of Table 6-12. Case 1 analyzes the effect of actual voluntary collaboration vis-à-vis neither collaboration nor funding. By collaborating for innovation, the collaborating companies increase their likelihood to patent by 10.7 percentage points, which is significantly positive. This substantial increase can be seen as the private return on voluntary collaboration. In case 2 we estimate the effect of funding on companies that only receive funding without engaging in collaborative innovation activities. Public funding increases their likelihood of filing for patents by almost 10 percentage points. The overall largest effect is obtained by collaboration and funding as depicted by case 3. It amounts to 26.8 percentage points. Companies that receive funding and conduct cooperative R&D activities would – if they had had neither – have experienced a likelihood to patent of about 27 percentage points less than the actual one.

Note that the probabilities to patent given on the diagonal of Table 6-12 are the probabilities of the actual state. The first element of the diagonal gives the probability to patent of all companies which have neither collaborated for innovation nor received funding. The probability is about 9.4 percent. After the matching, the counterfactual situation in case 3, for instance, indicates a probability of 18 percent (44.8 percent – 26.8 percent). This again highlights the fact that the average firm that has received funding and carried out collaborative research has a higher propensity to patent, even if the funding had not been granted and collaborative research had not been carried out – which is a further indication of the selection bias.

In case 6 the companies that have actually collaborated and received funding are analyzed for the effect that the funding exerted on their innovation output, assuming that their execution of collaborative R&D efforts remains unchanged. We observe that public funding has a significantly positive effect even on collaborating companies. Case 9 reverses this argument and asks if collaboration exerts an effect on the companies that are funded. Receiving funding and collaborating for R&D – relative to only receiving funding – increases the patenting probability by 12.7 percentage points.

Our analysis shows that actual funding and voluntary collaboration have a positive effect on the generation of innovative output. The analysis also suggests that actual public funding induces an increase in innovation output even in firms which are already collaborating.

As we have seen, the Finnish companies in the sample are smaller than the companies in the German sample, the analysis of which will be discussed below. The effect of public funding on top of collaboration may be due to the restricted access to external financing and capital markets that smaller companies tend to have. 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 did not decide to subsidize them. In this case, firms might not be able to raise enough capital to maintain their high innovation efforts. In addition, collaboration enhances the innovation output of funded firms. Overall the largest effects can be achieved if public funding and collaborative R&D go hand in hand.

6.2.5.2 Potential policy

In the analysis of potential policy we focus on the cases in Table 6-12 below the main diagonal. Case 4 takes the companies that actually neither collaborate nor receive funding and asks how their actual innovation output compares to the innovation output they would have received had they voluntarily collaborated for innovation.[37] Collaboration would have increased their innovation output significantly. More specifically, their probability to patent would have increased by 6.9 percentage points. Had the same group of companies not collaborated, but received funding without any incentive to collaborate instead, their innovation

[37] The negative sign is due to the definition of the impact which is the difference in output in the actual and counterfactual states (see e.g. equation (16) above). It indicates that the potential policy will have a positive effect.

output would have grown, although not significantly. Had the same group of companies received funding augmented with an incentive to collaborate, and had the same group followed the incentive, their innovation output would have expanded. Their likelihood to patent would have increased by 17.1 percentage points to an overall 26.4 percent.

The companies that have actually and voluntarily collaborated would not have increased their innovation output significantly, had they received funding (case 11). However, if the actually funded companies can be induced to collaborate, their likelihood to patent will increase by 14.6 percentage points.

Extending funding to the group of non-funded companies without an incentive for collaborative R&D would not yield significant positive effects on average.

6.2.5.3 Actual and potential policy

This section compares the actual and potential policies, based on the matching analysis. To facilitate the discussion, Table 6-13 reports the factual propensity to patent on the main diagonal and the counterfactual propensities to patent in all the other cells.

Table 6-13. Matching results for Finland: counterfactuals.

		Actual state (m)			
		None	Collaboration	Public funding	Both
Counterfactual state (l)	None	0.093	1) 0.113	2) 0.105	3) 0.180
	Collaboration	4) 0.162	0.220	5) 0.286	6) 0.367
	Public funding	7) 0.173	8) 0.213	0.203	9) 0.321
	Both	10) 0.264	11) 0.127	12) 0.349	0.448

Note: The main diagonal shows the unadjusted average probability to patent of the groups in columns. All other cells report the counterfactual probability to patent.

We have seen in section 6.2.5.2 above that some potential extension of the general policy could unleash significantly positive effects on innovation output.

In particular fostering voluntary collaboration among companies that are not yet collaborating can increase the innovative output, as we find that these companies can increase their patenting probability by 6.9 percentage points on average. In the counterfactual case, these companies yield a patenting probability of 16.2 percent. In addition, there are substantial effects to be expected by funding companies and inducing them to carry out collaborative R&D. On average, their innovation output measured by the probability to patent would increase by 17.1 percent from 9.3 percent to 26.4 percent. Inducing already funded companies to collaborate would – on average – increase their likelihood to patent by 14.6 percent to reach 34.9 percent.

Note that the success of these potential policy changes will not be immediately visible if one only observes the impact of actual policy measures. If R&D subsidies are granted to companies that are not currently funded, and if collaborative R&D is successfully induced, the average company will reveal an innovation output measured by its patenting probability of 26.4 percent. As we have discussed above, the underlying effect generated by the extension of funding to non-funded companies is 17.1 percentage points. However, the average patenting probability of the average by an extension of the current funding to a newly funded company is only 26.4 percent as compared to the 44.8 percent of currently subsidized and collaborating companies. The average newly subsidized companies will necessarily reduce the average probability of subsidized and collaborating companies. An examination of only the average innovation output of actually funded companies over time may lead to misguided conclusions about the effectiveness of the extension of funding. Careful analysis of the counterfactual situation is required to be able to assess the success or failure of a policy measure.

The above line of reasoning also applies to fostering voluntary collaboration and inducing the collaborative R&D of publicly funded companies. The underlying assumption above is that the policy measure is randomly applied to companies within the group of non-funded companies such that the average effect among these companies is a valid estimate of the effects to be expected. However, if there is a selection process determining the companies to be exposed to the policy measure – extension of the funding, inducing collaboration – the above caveat may not apply. The selection process may select the most promising companies, resulting in an above-average effect.

6.2.6 Results of the German sample

The average treatment effects for the German sample using the matching approach to construct the counterfactual situation are reported in Table 6-14. In the following sections we will first discuss the effects of actual policy and then turn to the effects caused by potential changes or extensions in the overall policy.

Table 6-14. Matching results for Germany: average treatment effects.

		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	

Note: Standard errors in parentheses. *** (**,*) indicates a 1% (5%, 10%) significance level (two-sided test). Standard errors are obtained with Lechner's (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.

6.2.6.1 Actual policy

For the German sample, we observe that collaboration and public funding in combination with collaboration for innovation has a positive effect, as compared to the counterfactual situation of neither collaboration nor funding. Funding alone has no significantly positive effect on the innovation output in the German sample. Interestingly, we observe that inducing the already funded companies to carry out collaborative innovation activities does not add to the innovation output here. In addition, the effect of public funding on already collaborating companies has a negative, yet insignificant, effect.

6.2.6.2 Potential policy

Inducing companies that are not yet collaborating for innovation to carry out their innovation activities together with other partners from industry or science would increase the innovation output, as we observe a positive effect of 13.2 percentage points on average. If the collaboration is induced with public funding, the effect is still positive and of the same magnitude.

6.2.7 Comparative analysis

Given the analysis of both the Finnish and German results above, we can investigate which effects occur in both countries and which effects are country-specific. However, this question by no means suggests that we can derive general conclusions about universal effects and country-specific effects. A larger sample of countries would have to be analyzed to derive results of this kind. The following analysis rather opens up discussion and allows us to see that the underlying rationale and working of the subsidies may be quite different, even though the overall structure of governmental intervention in innovation is rather comparable in Finland and Germany. Table 6-15 compares the effects of public funding and collaboration for innovation in the Finnish sample with the effects in the German sample.

Table 6-15. Comparing the effect in the Finnish and the German sample.

		Actual state (*m*)			
		None	Collaboration	Public funding	Both
Counterfactual state (*l*)	None		1) FI: + DE: +	2) FI: + DE: .	3) FI: + DE: +
	Collaboration	4) FI: - DE: -		5) FI: . DE: .	6) FI: + DE: .
	Public funding	7) FI: . DE: .	8) FI: . DE: .		9) FI: + DE: .
	Both	10) FI: - DE: -	11) FI: . DE: .	12) FI: - DE: .	

Note: + (-, .) indicate a positive, (negative, no) treatment effect in the sample of the respective countries. Bold face indicates comparable effects in the Finnish and the German sample.

6.2.7.1 Common effects

The common effects of actual policy in both countries are, first, that voluntary collaboration generates a positive impact on the output of innovation activities and, second, that public funding (once it goes hand-in-hand with collaborative R&D) has a significantly positive impact on innovation output. Concerning potential policy, both the Finnish and German samples agree that fostering voluntary collaboration among the not yet collaborating companies has a positive innovation output effect on average. Likewise, in both countries, public subsidies for innovation activities have potential for increasing innovation output if they are combined with the incentive to carry out collaborative R&D.

In both countries we also observe that an extension of public funding that is not accompanied by a strong incentive for cooperative innovation activities on average does not increase innovation output significantly. In addition, both the Finnish and German samples suggest that extending public funding to companies that are already collaborating does not increase the innovation output of the average funded firm.

6.2.7.2 Country-specific effects

We also observe that, in contrast to the German sample, the Finnish sample suggests that public funding, even without inducing collaboration, has a positive effect on the innovation output of funded firms and that, even if the companies already collaborate for innovation, public funding increases innovation output. We also observe that, in the Finnish samples on average, collaboration increases innovation output even among funded companies. In the German sample it does not do so. The analysis also shows that, in the German sample, collaboration of already funded companies does not significantly affect the innovation output of companies. In the Finnish sample, however, innovation output could increase by inducing already funded companies to start collaborative R&D.

6.2.7.3 Summary

Table 6-16 summarizes the actual effects of certain policies. It also highlights the average effects expected by potential policy measures.

Table 6-16. Innovation output effects of actual policy and policy options.

	Finland	Germany
Actual policy (effects realized)		
Induce voluntary collaboration with instruments other than funding	✓	✓
Fund companies without inducing collaboration for innovation	✓	
Fund companies which are already collaborating	✓	
Induce collaboration with already funded companies	✓	
Fund companies and induce collaboration simultaneously	✓	✓
Potential policy (potential effects)		
Induce voluntary collaboration among companies not yet collaborating and funded	✓	✓
Extend funding to companies that are not yet funded without inducing collaboration		
Extend funding to companies that are not yet funded and induce collaboration simult.	✓	✓
Extend funding to companies that are already collaborating		
Induce collaboration in companies that are already being funded	✓	

Note: ✓ indicates positive (expected) effects of the actual (potential) policies.

The effects highlighted in this part of the analysis are only the direct effects that occur at companies targeted by the policy measure. From the data at hand we cannot assess any effects of funding which do not directly occur at the funded firms.

6.3 A quasi-difference-in-difference estimation

Since we observe a high correlation between the lagged patent variable and the patenting variable, it seems intuitive to conduct a difference-in-difference estimation as a sensitivity analysis of the results in addition to the matching. As we have discussed in section 4.3.3, the difference-in-difference estimation is one possibility to control for firm-specific individual effects. However, as our lagged patent variable accounts for patent activity since 1985, we would clearly underestimate the treatment effects if we compared it with the patent outcome variable used in the sections above.

Moreover, as briefly mentioned above, the cross-sectional structure of our data does not allow the application of a *correct* difference-in-difference estimator. Having said this, we do not want to abandon the idea of correcting for firm-specific individual effects, but are rather content with a quasi-diffs-in-diffs estimation. Thus we construct a variable that takes the value 1 if a firm applied for a patent in the 3-year period prior to the observation period. It is zero otherwise. Computing the difference obviously indicates the change in patenting behavior over time. In contrast to matching, this approach has several advantageous features:

(1) It controls for firm-specific fixed effects that might contribute to firm performance by differencing them out.

(2) It does not rely on the conditional independence assumption.

(3) It is not affected by the common support restriction required in matching.

(4) This approach also rules out possible endogeneity that may affect the matching results due to the inclusion of an innovation input variable.

The diffs-in-diffs estimation performs a before-and-after comparison of treated firms, and compares their change in 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-diffs-in-diffs approach, since we do not observe the treatment status in the previous period because we only have cross-sectional information on it. Therefore, it is 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 receive it 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 this relates to only a small number of cases, causing a small bias which should play only a minor role in interpretation.

To show the change in patenting behavior as described above, we have created a discrete variable taking the values –1, 0 and 1 and interpreted as shown in Table 6-17.

Table 6-17. Interpretation of the change in patenting behavior.

	Patenting in t-1	Patenting in t
Change in patenting behavior = -1	yes	no
Change in patenting behavior = 0	yes	yes
	no	no
Change in patenting behavior = +1	no	yes

We estimate a multinomial probit model regressing the indicator for change in patenting behavior illustrated in Table 6-17 on the three dummy variables for public funding (only), for collaboration (only) and for both funding and collaboration. We include the non-treated firms. This amounts to the diffs-in-diffs 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 where no change in patenting behavior can be observed. The results are presented for the Finnish and German samples in Table 6-18 and Table 6-19 respectively.

Table 6-18. Difference-in-difference estimation; Finnish sample.

	DIFF = – 1		DIFF = +1	
	Coef.	Std. err.	Coef.	Std. err
Public funding (only)	0.193	0.192	0.518 ***	0.165
Cooperation (only)	–0.263	0.173	0.427 ***	0.131
Public funding and cooperation	0.129	0.137	0.843 ***	0.118
Constant term	–1.689 ***	0.109	–1.594 ***	0.103
LR-Test on RHO = 0	$\chi 2(1)$ = 23.903 ***			

Note: *** (**, *) indicates a significance level of 1% (5%, 10%); 200 draws from the simulator. N = 1,520.

In Finland the estimates show that funding, collaboration, and both collaboration and funding generate a higher likelihood to change from no patent applications to at least one patent application. The analysis here is broadly in line with the findings in the matching estimations documented above. However, without investigating the marginal effects, it still seems that the largest influence in changing patenting behavior from no patenting to patenting is due to funding and collaboration simultaneously. This is also in accordance with the findings for the Finnish sample above.

Table 6-19. Difference in difference estimation; German sample.

	DIFF = – 1		DIFF = +1	
	Coef.	Std. err.	Coef.	Std. err
Public funding (only)	–0.220	0.200	0.204	0.133
Cooperation (only)	–0.175	0.149	0.481 ***	0.099
Public funding and cooperation	–0.028	0.168	0.309 **	0.123
Constant term	–1.511 ***	0.065	–1.116	0.053
LR-Test on RHO = 0	$\chi2(1)$ = 23.903 ***			

Note: *** (**, *) indicates a significance level of 1% (5%, 10%); 200 draws from the simulator. N = 1,464.

In Germany, the coefficients of the collaboration variable and the coefficient of the variable indicating both collaboration and funding are significantly different from zero for a change from non-patenting to patenting. This implies positive treatment effects for these groups. For public funding we cannot support the hypothesis of a positive treatment effect in this diffs-in-diffs setting. The effects in the German sample observed in the diffs-in-diffs setting here are in accord with the findings of the matching analysis (which also does not support positive effects of public funding alone). However, collaboration has a strong impact on the innovative performance of firms.

6.4 Summary

Complementing section 5, this section shows that in the sample of Finnish firms considerable output effects are realized by public subsidies for innovation activities. At the same time we are able to distinguish the effects generated by collaboration from the effects due to public funding. As far as the available cross-section data permitted, we checked the robustness of the results using a quasi-difference-in-difference estimation which – at least partially – controls for firm-specific effects. The quasi-diffs-in-diffs estimation confirmed the results obtained through the matching approach.

For our sample of Finnish firms, we find that collaboration, public funding and both of them together induce higher innovation output. We also find that collaboration adds to the effects of public subsidies and that public funding increases the output of firms already engaged in collaborative innovation activities.

The fact that the actual receipt of public funding has a positive effect on both collaborating and non-collaborating firms suggests that financial constraints for innovation activities are overcome or softened by the subsidies, which translates into increased innovation output.

For the Finnish sample, we also find that collaboration exerts a positive effect on the innovation output of funded and non-funded companies, supporting the idea that incentives for collaboration within the funding schemes increase the innovative output and effect of funding.

The assessment of potential policy is threefold. Fostering voluntary collaboration for innovation among companies not yet collaborating will increase the overall innovation output. On average, public funding alone will not yield any significant effects. However, if public subsidies are used as a measure to force companies into cooperative innovation activities, they will yield a positive effect on innovation output.

Finally, our findings that collaboration and public funding have a positive effect on innovation output are in line with Branstetter and Sakakibara (2002), Czarnitzki and Fier (2003), Czarnitzki and Hussinger (2004), Ebersberger (2004b) and Ebersberger and Lehtoranta (2005).

7. Conclusion

________ *This section concludes the analysis by summarizing the findings of the previous sections. It does so not only by recapitulating the findings but also by making an important addition to the empirical analysis that ties together the findings of input additionality from section 5 with the findings of output additionality from section 6.* ______________________

7.1 Findings of the study

This study investigates the input additionality and output additionality of the Finnish government's intervention in private sector innovation activities. The general empirical approach employed in this study consists of a matching analysis in which governmental intervention is interpreted as a treatment. For each treated firm the matching analysis finds an untreated company which is comparable to a treated one. The difference in behavior of the treated and non-treated firms is an estimate for the impact of the treatment. In section 5 the treatment is the firm's receipt of public funding. There the focus is on input additionality and it investigates whether funded companies invest more in R&D than they would have done without public funding. In section 6 we turn our attention to output additionality. The focus of the analysis is whether public funded companies realize a higher output than they would have done if they had not received any funding. As the funding agencies implement funding schemes exhibiting strong incentives for cooperative R&D we have to disentangle the effect of public funding from the effect of collaboration. The empirical analysis compares the findings with findings form other countries. For its particular similarity in terms of the structure of the funding system and the policy instruments employed, Germany is used for particularly detailed comparisons.

7.1.1 Input additionality

The analyses show that public subsidies induce Finnish firms to spend more on innovation than they would do without the subsidies. Public funding exhibits a strong input additionality effect.

Based on the results of the analyses we can reject the complete or partial crowding out. The results suggest complementarity of public funding and private innovation expenditure. The results are in line with the findings for a comparable set of German companies. The effect is of comparable magnitude to the effect in the analysis of the German sample. Heckman selection models obtain quantitatively similar results, suggesting that the assumptions underlying the matching approach are not grossly violated.

The reasons for this remarkable input additionality can be explained by determinants within the subsidized firm, by determinants outside the subsidized firm and in the decision principals of the funding agency. Within each firm, the receipt of public subsidies has a strong bearing on internal arguments in favor of a funded project (see e.g. Luukkonen and Hälikkä 2000). Positive funding decision may not only shift the priorities between potential R&D projects, which would not result in any additionality, but also shift priorities with respect to projects unrelated to R&D. This shift causes increasing innovation intensity as a result of the public funding decision. This line of reasoning may be especially relevant for larger firms.

Factors in the business environment may affect the additionality of public funding for small and medium sized enterprises in particular. As argued in Hyytinen and Toivanen (2003) there are market imperfections in the financial markets, exposing SMEs to financial constraints for innovation activities. Public funding may be a means of alleviating these financing constraints. The effect that SMEs particularly benefit from subsidies supports the idea that public R&D subsidies act as leverage for SMEs to tap into other sources of financing. Lerner (1999) points out that receiving a public R&D grant serves as a quality indicator of the firm's R&D efforts. This may reduce the threshold especially for SMEs to acquire more funding for their innovation efforts from the financial markets.

We also observe that the increased nominal input in R&D – R&D expenditure – translates into an increased real input in R&D – R&D personnel.

7.1.2 Output additionality

The analyses show that, in the sample of Finnish firms, considerable output effects are realized by public subsidies for innovation activities.

At the same time, we are able to distinguish the effects generated by collaboration from the impact of public funding. As far as the available cross-section data permitted, we checked the robustness of the results using a quasi-difference-in-difference estimation which – at least partially – controls for firm-specific effects. The quasi-diffs-in-diffs estimation confirmed the results obtained by applying the matching approach.

For our sample of Finnish firms, we find collaboration, public funding and both of them together inducing higher innovation output. Collaboration adds to the effects of public subsidies and public funding increases the output of firms already engaged in collaborative innovation activities.

The fact that the actual receipt of public funding has a positive effect on both collaborating and non-collaborating firms suggests that financial constraints for innovation activities are overcome or softened by subsidies, which translates into increased innovation output.

For the Finnish sample, we also find that collaboration exerts a positive effect on the innovation output of funded and non-funded companies, supporting the idea that incentives for collaboration within the funding schemes increase the innovative output and effect of funding.

The assessment of potential policy suggests three issues:

(1) Fostering voluntary collaboration for R&D among companies not yet collaborating will increase overall innovation output.

(2) On average, public funding alone will not yield any significant effects.

(3) However, if public subsidies are used as a measure to force companies into cooperative innovation activities, they will yield a positive effect on innovation output.

7.2 Relating input additionality and output additionality

The analysis above contains convincing evidence that public funding generates input additionality effects and output additionality effects separately. However, to be able to argue in support of the Lisbon strategy that an increase in public funding and an increase in innovation expenditure in general have a bearing on the innovativeness and productivity of an economy we have to establish a relationship between the increased efforts on the input side and the increased output. Although this is quite plausible in the light of the evidence presented here, it does not necessarily follow from the results so far.

To be able to conclude that the approach taken supports the strategic targets, we have to investigate how increased innovation input translates into higher innovation output. The results generated in section 5 enable us to investigate how increased input translates into innovation output. Phrased differently, we want to investigate whether the additional input generated by the subsidy contributes to increasing the innovation output. Table 7-1 contains an analysis on how innovation input affects innovation output which is – in line with section 6 – proxied by the patenting behavior of firms. The innovation input is split into two parts:

(1) Private innovation expenditure, i.e. the innovation expenditure a subsidized firm would have spent if it had not been subsidized. For non-funded companies it is the observed R&D expenditure.

(2) Additional innovation expenditure, i.e. the subsidy and additionally induced private funding.

We report the coefficients of regressing the patenting behavior as a dummy variable on the R&D expenditure, split up as introduced above and on time and sectoral dummy variables in Table 7-1.

Table 7-1. Relating input additionality to output additionality.

	All observations		SMEs only	
	Coeff.	Std. err.	Coeff.	Std. err
Private innovation expenditure	0.010***	0.002	0.015*	0.009
Additional innovation expenditure	0.009***	0.003	0.031***	0.007
Time dummy (Year = 2000)	0.140*	0.074	0.340***	0.081
Number of observations	1,444		1,155	
Wald chi^2	138.53***		137.25***	

Note: Probit model performed only on innovating companies, *** (**, *) indicates a significance level of 1% (5%, 10%). The analysis also includes nine sectoral dummies the estimation results for which are not reported here. Standard errors are bootstrapped with 200 replications.

For all observations, private innovation expenditure and additional innovation expenditure both have a significantly positive effect on a firm's patenting probability. Both effects do not differ in size. For the sub-sample of SMEs, we also find a positive effect of private innovation expenditure and the additional innovation expenditure induced by public funding. However, the marginal effect[38] of the latter on patenting probability is significantly larger than the marginal effect of the former. It is twice as large. We interpret this result as indicating that SMEs, which can be seen as notoriously financially constrained, are pushed over a threshold for financing R&D by public subsidies. These subsidies leverage an additionality effect which allows the SMEs to yield increasing returns on their innovation activities.

The results obtained here are in line with the findings of Czarnitzki and Hussinger (2004) who find a positive relationship between the additional R&D efforts triggered by public funding and the innovation output of German firms.

7.3 Overall assessment

Concerning the overall effects of public funding in Finland we can draw quite positive conclusions based on our empirical analysis:

(1) On average, public funding increases the private innovation effort of funded firms, in both nominal and real terms.

(2) On average, public funding increases the innovation output of funded firms. Public funding yields the largest effects when it stimulating collaborative innovation activities.

(3) An increased private innovation effort increases innovation output on average.

A policy option that we have identified in the analysis of section 6 is that, on average, inducing voluntary collaboration could yield positive effects. However, in light of the fact that collaboration density is rather high in the Finnish

[38] The marginal effects are not reported in Table 7-1.

innovation system by international standards, there may be limits to increasing the propensity to collaborate for innovation. Funding for the collaborative R&D of companies not yet actively collaborating may be an option for increasing innovative output.

Although we find positive effects of funding, regardless of the collaboration status, the analysis suggests that, on average, handing out funding to companies that are not yet funded will not result in an increase in innovation output if it fails to induce non-collaborating firms to engage in collaboration for innovation. We also expect no effect from extending funding to companies that are already engaged in collaborative R&D.

Even though the employed analytical tools succeeded in generating interesting results from the Community Innovation Survey, there are limitations to our study which cannot be overcome with the data available at statistical offices.

First and foremost, the analysis conducted here only looks at the direct effects. It does not take account of effects that might occur elsewhere outside the funded firms, such as network effects, knowledge spillovers, and the increase in the national capacity to innovate. These are beyond what can be tackled with the given data. However, the effects are certainly not beyond what is generally feasible and interesting to the researcher and the policy maker alike.

Second, this study confined itself to an analysis of the average. The effects that occur at a few firms, or just one firm, are not recorded as significant effects here. By using the set of econometric tools as they are, we completely override the argument that in some cases a single success story may make a whole funding program worthwhile. More detailed analysis with data from other sources, such as data gathered by the funding agency, may alleviate this concern.

Future work could try to merge register-based data, innovation survey data and project- and firm-level data from the funding agencies, in order to paint a more colorful picture on the size and kind of public funding than is depicted by just the zero/one variable this study essentially had at its disposal.

Third, this last point raises a question as to whether the average is the interesting statistic in all cases of impact assessment. Other statistics such as the median may be even more interesting to the policy maker who wishes to see the effects of public funding. Generally, one may be interested in how governmental intervention affects the whole population of firms. This question is only partially answered in this study and could be extended in future work.

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Appendix A: CIS III Questionnaire

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The Third Community Innovation Survey
(CIS III)

CORE QUESTIONNAIRE

The Third Community Innovation Survey **(Version 6: 20 February 2001)**

This survey collects information about new or significantly improved products or processes and related activities in manufacturing and service industries during the period 1998-2000. In order to be able to compare enterprises with and without innovative activities, we request all enterprises to respond to all questions, unless otherwise instructed.

If you have any questions or doubts concerning this questionnaire please contact:

Mrs. / Mr. __________

Phone : __________
Fax : __________
e-mail : __________

Name of respondent __________
Job title __________
Phone __________
Fax __________
e-mail __________

General information about the enterprise

An enterprise is defined as the smallest combination of legal units that is an organisational unit producing goods or services. An enterprise carries out one or more activities at one or more locations. An enterprise may be a sole legal unit.

Name of enterprise ____________________

Address[1] ____________________

Postal code __________ **Main activity** ____________________

0.1 Is the enterprise part of an enterprise group?

Yes =>What is the country of head office of the group?[2] ________

No

0.2 Did any of the following significant changes occur to your enterprise during the period 1998-2000?

	Yes	No
Your enterprise was established		
Turnover increased by 10 % or more due to merger with another enterprise or part of it		
Turnover decreased by 10 % or more due to sale or closure of part of the enterprise		

OPT. 0.3 Please indicate what is the average lifetime of your enterprise's most important product (good or service) before it is replaced or being significantly modified:

Less than 1 year 1-3 years 4-6 years 7-9 years More than 9 years Impossible to answer

0.4 What is your enterprise's most significant market *Please tick the most appropriate alternative*

Local/ regional (within a distance of around 50 km) within your country

Local/ regional (within a distance of around 50 km) within your neighbouring countries

National (with a distance of more than 50 km)

International (with a distance of more than 50 km)

[1] NUTS 2 code has to be supplied to Eurostat

[2] Country code according to ISO standard has to be supplied to Eurostat

Basic economic information on the enterprise
(Only units located in the country in which you are reporting should be included)

0.5 Total turnover[3] market sales of goods and services Including export and taxes except VAT (in national Currency units)

	In year **1998**	In year **2000**
0.5	☐☐☐☐☐☐☐☐ 000,-	☐☐☐☐☐☐☐☐ 000,-

0.6 Exports of goods and services
(in national currency units)

	In year **1998**	In year **2000**
0.6	☐☐☐☐☐☐☐☐ 000,-	☐☐☐☐☐☐☐☐ 000,-

0.7 Gross investment in tangible goods[4]
(in national currency units)

	In year **1998 (OPT)**	In year **2000**
0.7	☐☐☐☐☐☐☐☐ 000,-	☐☐☐☐☐☐☐☐ 000,-

0.8 Number of employees[5]

	In year **1998**	In year **2000**	OPT Expected change for year **2002**
0.8.1 Total number of employees	☐☐☐☐☐	☐☐☐☐☐	**No Change** **Reduction** **Increase** = ☐☐ %
Of which: With Higher education **(graduated from tertiary education)**			
- 0.8.2 Total		☐☐☐☐☐	**No Change** **Reduction** **Increase** = ☐☐ %
- 0.8.3 of which: Female (OPT)		☐☐☐☐☐	

[3] For Credit institutions: Interests receivable and similar income; for Insurance services: Gross premiums written
[4] Acquisition of machinery and equipment, building and land
[5] Annual average. If not available, number of employees at the end of the year can be used

Innovation

An innovation, as defined in this survey, is a new or significantly improved product (good or service) introduced to the market or the introduction within your enterprise of a new or significantly improved process. The innovation is based on the results of new technological developments, new combinations of existing technology or utilisation of other knowledge acquired by your enterprise.

1. Product innovation

Product innovation is a good or service which is either new or significantly improved with respect to its fundamental characteristics, technical specifications, incorporated software or other immaterial components, intended uses, or user friendliness.
The innovation should be new to your enterprise; it has not necessarily to be new to the market. It does not matter whether the innovation was developed by your enterprise or by another enterprise. Changes of a solely aesthetically nature, and purely selling of innovations wholly produced and developed by other enterprises, shall not be included.
For examples of innovations see Annex.

1.1 During the period 1998-2000, did your enterprise introduce onto the market any new or significantly improved products (goods or services) for your enterprise ?

Yes => **Who developed these products?** *Please tick the most appropriate alternative*
- Mainly your enterprise or enterprise group
- Your enterprise in co-operation with other enterprises or institutions
- Mainly other enterprises or institutions

No => go to question **2**.

1.2 Please give a short description of what is new or significantly improved with your most important product (good or service) innovation.

____
____
____

1.3 Please estimate how your turnover[6] in 2000 was distributed between

- New or significantly improved products (goods or services) introduced during the period 1998–2000	[ ][ ][ ]	%
- Unchanged or only marginally modified products (goods or services) during the period 1998–2000[7]	[ ][ ][ ]	%
Total turnover in 2000	1 0 0	%

1.4 During the period 1998-2000, did your enterprise introduce new or significantly improved products (goods or services) not only new for your enterprise, but also new for your enterprise's market?

Yes =>Please estimate the contribution of these products in total turnover[6] in 2000: [ ][ ][ ] %
No

[6] For Credit institutions: Interests receivable and similar income; for Insurance services: Gross premiums written
[7] Products wholly developed and produced by others shall be included here

2. Process innovation

Process innovation includes new and significantly improved production technology, new and significantly improved methods of supplying services and of delivering products. The outcome should be significant with respect to the level of output, quality of products (goods/services) or costs of production and distribution.
The innovation should be new to your enterprise; your enterprise has not necessarily to be the first to introduce this process. It does not matter whether the innovation was developed by your enterprise or by another enterprise. Purely organisational or managerial changes shall not be included.
For examples of innovations see Annex.

2.1 During the period 1998-2000, has your enterprise introduced any new or significantly improved production processes including methods of supplying services and ways of delivering products?

Yes => **Who developed these processes?** *Please tick the most appropriate alternative*
Mainly your enterprise or enterprise group
Your enterprise in co-operation with other enterprises or institutions
Mainly other enterprises or institutions
No => go to question **3.**

2.2 Please give a short description of what is new or significantly improved with your most important process innovation.

____
____
____

3. Not yet completed or abandoned innovation activities

3.1 By the end of 2000, did your enterprise have any ongoing activities to develop or introduce new or significantly improved products (goods or services) or processes that were not yet completed, including any R&D activity ?

Yes
No

3.2 During the period 1998-2000, did your enterprise have any activities to develop or introduce new or significantly improved products (goods or services) or processes that were abandoned, including any R&D activity?

Yes
No

Enterprises with no recent innovation activity (ie. answered No to each of questions 1.1, 2.1, 3.1 or 3.2), should now go question 10.1b.

4. Innovation activity and expenditure in 2000

4.1 Did your enterprise engage in the following innovation activities in 2000?		**Yes**	**No**	**If yes**
Please tick "yes" for the following innovation activities if applied by your enterprise in 2000 by implementing new or significantly improved products (goods/ services) or processes based on science, technology or other knowledge areas. Subsequently, give an estimate of the related expenditures in 2000, including not yet completed or abandoned innovation activities. Tick "no" for activities not undertaken in 2000.				Please estimate innovative expenditure in 2000, incl. personnel and related investment expenditures (no depreciation) – national currency
Intramural research & experimental development (R&D)	All creative work undertaken within your enterprise on a systematic basis in order to increase the stock of knowledge, and the use of this stock of knowledge to devise new applications, such as new and improved products (goods/ services) and processes (including software research)			000,-
Acquisition of R&D (extramural R&D)	Same activities as above, but performed by other companies (including other enterprises within the group) or other public or private research organisations			000,-
Acquisition of machinery and equipment	Advanced machinery, computer hardware specifically purchased to implement new or significantly improved products (goods/services) and/or processes			000,-
Acquisition of other external knowledge	Purchase of rights to use patents and non-patented inventions, licenses, know-how, trademarks, software and other types of knowledge from others for use in your enterprise's innovations			000,-
Training	Internal or external training for your personnel directly aimed at the development and/or introduction of innovations			000,- (combined for Training, Market introduction of innovations, and Design)
Market introduction of innovations	Internal or external marketing activities directly aimed at the market introduction of your enterprise's new or significantly improved products (goods/services), (may include preliminary market research, market tests and launch advertising, but exclude the building of distribution networks to market innovations)			
Design, other preparations for production/deliveries	Procedures and technical preparations to realise the actual implementation of products (goods/services) and process innovations not covered elsewhere			
	Total innovation expenditure in 2000 *(in national currency units)*			000,-

5. Intramural research and experimental development (R&D)

If you have Intramural R&D-activities:

5.1 How many persons were involved in intramural R&D activities within your enterprise in 2000?
(including persons both inside and outside your R&D department)
(in full time equivalents) : ☐☐☐☐

5.2 How did your enterprise engage in R&D during 1998-2000?

Continuously
Occasionally

6. Effects of innovation during 1998-2000

The result of innovation activity may have different effects for your enterprise. *For the various alternatives, please indicate the degree of impact at the end of 2000 by innovation activity undertaken by your enterprise during the period 1998-2000.*

		Degree of impact			
		High	Medium	Low	Not relevant
Product oriented effects	Increased range of goods or services				
	Increased market or market share				
	Improved quality in goods or services				
Process oriented effects	Improved production flexibility				
	Increased production capacity				
	Reduced labour costs per produced unit				
	Reduced materials and energy per produced unit				
Other effects	Improved environmental impact or health and safety aspects				
	Met regulations or standards				

7. Public funding of innovation

Public funding includes financial support in terms of grants and loans, including a subsidy element, and loan guarantees. Ordinary payments for orders of public customers shall not be included.

7.1 Did your enterprise receive any public financial support for innovation activities during the period 1998-2000?

From:	Yes	No
Local or regional authorities		
Central government (including institutions working on behalf of central government)		
The European Union		

7.2. Has your enterprise received funding from the EU's 4th (1994-98) **or 5th** (1998-2002) **Framework Programmes for RTD?**

Yes

No

8. Innovation co-operation during the period 1998-2000

Innovation co-operation means active participation in joint R&D and other innovation projects with other organisations (either other enterprises or non-commercial institutions). It does not necessarily imply that both partners derive immediate commercial benefit from the venture. Pure contracting out of work, where there is no active collaboration, is not regarded as co-operation.

8.1 Did your enterprise have any co-operation arrangements on innovation activities with other enterprises or institutions during 1998-2000?

Yes

No => go to question **9**

8.2 Please indicate the type of organisation and location

Multiple answers possible

Type of partner	National	EU*/ EFTA**	EU-CC***	US	Japan	Other
Other enterprises within your enterprise group						
Suppliers of equipment, materials, components or software						
Clients or customers						
Competitors and other firms from the same industry						
Consultants						
Commercial laboratories /R&D enterprises						
Universities or other higher education institutes						
Government or private non-profit research institutes						

* : European Union countries(Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland, Sweden and the United Kingdom)

** European Free Trade Association countries (Iceland, Liechtenstein, Norway, Switzerland)

*** EU Candidate Countries (Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovak Republic, Slovenia Republic and Turkey)

OPT. 8.3 Please indicate the importance of your partners

Type of organisation partner	High	Medium	Low	No partner
Other enterprises within your enterprise group				
Suppliers of equipment, materials, components or software				
Clients or customers				
Competitors and other firms from the same industry				
Consultants				
Commercial laboratories /R&D enterprises				
Universities or other higher education institutes				
Government or private non-profit research institutes				

9. Sources of information for innovation during the period 1998-2000

The main sources of information needed for suggesting new innovation projects or contributing to the implementation of existing projects are asked in this question. *Please indicate the degree of importance attached to various alternative information sources*

INFORMATION SOURCE		If used, importance			Not used
		High	Medium	Low	
Internal sources	Within the enterprise				
	Other enterprises within the enterprise group				
Market sources	Suppliers of equipment, materials, components or software				
	Clients or customers				
	Competitors and other enterprises from the same industry				
Institutional Sources	Universities or other higher education institutes				
	Government or private non-profit research institutes				
Other sources	Professional conferences, meetings, journals				
	Fairs, exhibitions				

10. Hampered innovation activity

10.1a. During the period 1998-2000 was any of your innovation activity:

♂	seriously delayed?	Yes	No
♂	prevented to be started?	Yes	No
♂	burdened/cumbered with other serious problems?	Yes	No

Go to question 10.2

Absence of innovation activity

10.1b. During the period 1998-2000 were any of the following reasons relevant for your firm not having any innovation activity at all:

♂	no need due to prior innovations?	Yes	No
♂	no need due to market conditions?	Yes	No
♂	factors impeding innovation?	Yes	No

Factors hampering innovation activity

10.2 If your enterprise experienced any hampering factors during the period 1998-2000, please grade the importance of the relevant factors *(you may tick more than one factor if necessary).*

HAMPERING FACTORS		Degree of importance High	Medium	Low	Not relevant
Economic factors	Excessive perceived economic risks				
	Innovation costs too high				
	Lack of appropriate sources of finance				
Internal factors	Organisational rigidities within the enterprise				
	Lack of qualified personnel				
	Lack of information on technology				
	Lack of information on markets				
Other factors	Insufficient flexibility of regulations or standards				
	Lack of customer responsiveness to new goods or services				

11. Patents and other protection methods

11.1a During the period 1998-2000, did your enterprise, or enterprise group, apply for at least one patent to protect inventions or innovations developed by your enterprise?

			Total (*Goods /services/ processes)*	Of which: *Goods /services*
Yes	=>	**OPT.** Please indicate the number of patent applications[8]		
No				

11.1b Did your enterprise, or enterprise group, have any valid patents at the end of 2000 protecting inventions or innovations developed by your enterprise?

			Total (*Goods /services/ processes)*	Of which: *Goods /services*
Yes	=>	**OPT.** Please indicate the number of valid patent [8]		
No				

OPT 11.1c What percentage of your turnover in 2000 was covered by patent applications or patents valid at the end of 2000 owned by your enterprise or enterprise group?

Share of turnover in 2000 ______ % Impossible to answer

11.2 During the period 1998-2000, did your enterprise, or enterprise group, make use of any of these other methods to protect inventions or innovations developed in your enterprise?

		Yes	No
Formal methods	Registration of design patterns		
	Trademarks		
	Copyright		
Strategic methods	Secrecy		
	Complexity of design		
	Lead-time advantage on competitors		

[8] Patent application/patent for the same invention to different patent offices shall only be counted as one patent application/patent

12. Other important strategical and organisational changes in your enterprise

This survey has so far only dealt with new and significantly improved products (goods and services) and processes. This final question refers to other creative improvements that might have been undertaken by your enterprise.

12.1 Did your enterprise during the period 1998-2000 undertake any of the following activities:

		Yes	No
Strategy	Implementation of new or significantly changed corporate strategies		
Management	Implementation of advanced management techniques within your enterprise		
Organisation	Implementation of new or significantly changed organizational structures		
Marketing	Changing significantly your enterprise's marketing concepts/strategies		
Aesthetic change (or other subjective changes)	Significant changes in the aesthetic appearance or design or other subjective changes in at least one of your products		

Appendix B: Industry dummies

Table B-1 contains a breakdown of the whole sample in industries. The corresponding dummy variables are used in the regression analysis.

Table B-1. Definition of industries.

Ind.	Nace	Description
1	15.1, 15.3, 15.4, 15.5, 15.6, 15.7, 15.8, 15.9, 17.2, 17.3, 17.4, 17.5, 17.6, 17.7, 18.2, 18.3, 19.1, 19.2, 19.3	Production, processing and preserving of meat and meat products, Processing and preserving of fruit and vegetables, Manufacture of vegetable and animal oils and fats, Manufacture of dairy products, Manufacture of grain mill products, starches and starch products, Manufacture of prepared animal feeds, Manufacture of other food products, Manufacture of beverages, Textile weaving, Finishing of textiles, Manufacture of made-up textile articles, except apparel, Manufacture of other textiles, Manufacture of knitted and crocheted fabrics, Manufacture of knitted and crocheted articles, Manufacture of other wearing apparel and accessories, Dressing and dyeing of fur; manufacture of articles of fur, Tanning and dressing of leather, Manufacture of luggage, handbags and the like, saddlery and harness, Manufacture of footwear
2	20.1, 20.2, 20.3, 20.4, 20.5, 21.1, 21.2, 22.1, 22.2, 36.1, 36.2, 36.4, 36.6	Sawmilling and planing of wood; impregnation of wood, Manufacture of veneer sheets; manufacture of plywood, laminboard, particle board, fiber board and other panels and boards, Manufacture of builders carpentry and joinery, Manufacture of wooden containers, Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials, Manufacture of pulp, paper and paperboard, Manufacture of articles of paper and paperboard, Publishing, Printing and service activities related to printing, Manufacture of furniture, Manufacture of jewelry and related articles, Manufacture of sports goods, Miscellaneous manufacturing n.e.c.
3	23.2, 23.3, 24.1, 24.3, 24.4, 24.6, 24.7, 25.1, 25.2	Manufacture of refined petroleum products, Processing of nuclear fuel, Manufacture of basic chemicals, Manufacture of paints, varnishes and similar coatings, printing ink and mastics, Manufacture of pharmaceuticals, medicinal chemicals and botanical products, Manufacture of other chemical products, Manufacture of manmade erfibres, Manufacture of rubber products, Manufacture of plastic products
4	26.1, 26.2, 26.4, 26.5, 26.6, 26.7, 26.8	Manufacture of glass and glass products, Manufacture of non-refractory ceramic goods other than for construction purposes; manufacture of refractory ceramic products, Manufacture of bricks, tiles and construction products, in baked clay, Manufacture of cement, lime and plaster, Manufacture of articles of concrete, plaster and cement, Cutting, shaping and finishing of ornamental and building stone, Manufacture of other nonmetallic mineral products
5	27.1, 27.2, 27.3, 27.4, 27.5, 28.1, 28.2, 28.3, 28.5, 28.6, 28.7	Manufacture of basic iron and steel and of ferroalloys, Manufacture of tubes, Other first processing of iron and steel, Manufacture of basic precious and nonferrous metals, Casting of metals, Manufacture of structural metal products, Manufacture of tanks, reservoirs and containers of metal; manufacture of central heating radiators and boilers, Manufacture of steam generators, except central heating hot water boilers, Treatment and coating of metals; general mechanical engineering, Manufacture of cutlery, tools and general hardware, Manufacture of other fabricated metal products
6	29.1, 29.2, 29.3, 29.4, 29.5, 29.6, 29.7	Manufacture of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines, Manufacture of other general purpose machinery, Manufacture of agricultural and forestry machinery, Manufacture of machine tools, Manufacture of other special purpose machinery, Manufacture of weapons and ammunition, Manufacture of domestic appliances n.e.c.

Ind.	Nace	Description
7	30.0, 31.1, 31.2, 31.3, 31.5, 31.6, 32.1, 32.2, 32.3, 33.1, 33.2, 33.3, 33.4	Manufacture of office machinery and computers, Manufacture of electric motors, generators and transformers, Manufacture of electricity distribution and control apparatus, Manufacture of insulated wire and cable, Manufacture of lighting equipment and electric lamps, Manufacture of electrical equipment n.e.c., Manufacture of electronic valves and tubes and other electronic components, Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy, Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods, Manufacture of medical and surgical equipment and orthopaedic appliances, Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment, Manufacture of industrial process control equipment, Manufacture of optical instruments and photographic equipment
8	34.1, 34.2, 34.3, 35.1, 35.2, 35.3, 35.4, 35.5	Manufacture of motor vehicles, Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers, Manufacture of parts and accessories for motor vehicles and their engines, Building and repairing of ships and boats, Manufacture of railway and tramway locomotives and rolling stock, Manufacture of aircraft and spacecraft, Manufacture of motorcycles and bicycles, Manufacture of other transport equipment n.e.c.
9	64.2, 72.1, 72.2, 72.3, 72.4, 73.1, 73.2, 74.2, 74.3	Telecommunications, Hardware consultancy, Software consultancy and supply, Data processing, Database activities, Research and experimental development on natural sciences and engineering, Research and experimental development on social sciences and humanities, Architectural and engineering activities and related technical consultancy, Technical testing and analysis

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The Impact of Public R&D Funding

Abstract

This study investigates the effects of public R&D funding on the funded firms in Finland. It focuses on the input additionality, the output additionality of public funding and the effect an increase of innovation effort has on the innovation output of firms. The data set for this analysis is taken from the Community Innovation Survey which allows us to compare the results obtained with results obtained for other countries. For reasons discussed in the study the Finnish results are checked against results obtained for analyses of the Community Innovation Survey in Germany.

Concerning the overall effects of public funding in Finland we can draw quite positive conclusions based on our empirical analysis: First, on average, public funding increases the private innovation effort of funded firms, in both nominal and real terms. Second, on average, public funding increases the innovation output of funded firms. Public funding yields the largest effects when it stimulating collaborative innovation activities. Finally, an increased private innovation effort increases innovation output on average.

Keywords
research and development, funding, public subsidies, innovations, innovation expenditure, innovation output, innovation policy, governmental intervention, taxation, grants

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