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The Effect of Subsidies on R&D Investment and Success – Do Subsidy History and Size Matter?

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Non-technical Summary

Governments employ different instruments to support private R&D activities in order to increase firms' R&D efforts and innovative performance. The most important measure used by the German Federal Government to fund R&D in private businesses is the so-called *D*irect R&D *P*roject *F*unding (DPF). This paper contributes to the discussion of the effects and effectiveness of DPF as an innovation policy instrument by empirically analyzing the impact of DPF grants on firm's R&D input as well as on R&D output.

In the analysis I allow for heterogeneous effects to a certain extent in two dimensions: firm's DPF history and DPF grant size. Previous research reveals that the subsidization of firms via the DPF scheme shows a certain level of continuity. I investigate whether this rather stable pattern of program participation has an impact on the effectiveness of the scheme, i.e. whether the continuity of funding can be justified by its higher impacts. A second focus is set on the role of the grant size. Previous research for Ireland shows that the effects of grants on R&D input vary by grant size. This relationship is analyzed for the DPF grants in Germany. In addition, the effects on R&D output are examined to verify whether the public money is translated successfully into new products.

The empirical analysis is based on an annual innovation survey which is the German part of the Community Innovation Survey (CIS). This data is merged with a database comprising of information on subsidized projects in order to identify a firm's subsidy status for each year. The sample consists of over 8,500 firm-year observations covering the manufacturing and knowledge-intensive service sectors in the time period from 1994 to 2005. A non-parametric matching approach with multiple treatments is employed in the first step to provide insights into the impact of R&D grants on firm-financed R&D inputs, namely private R&D expenditures. In the second step the effect on R&D output, namely sales with products new to the market is examined, distinguishing the effect with respect to firm's DPF history and DPF grant size.

Overall a positive effect of DPF grants on R&D input and also on output is found. Thus the main policy goal of the DPF scheme i.e. to increase private investment in R&D is being achieved. However, not every grant has the same effect. The analysis provides evidence that (at least) the effect varies with firm's history of subsidies and grant size. Besides the necessity of a minimum grant size, the effect of private R&D increases with the frequent receipt of grants. For analyzing the effects of public grants on a firm's R&D output, R&D expenditures are disentangled in R&D which would have been spent in the absence of the grant and publicly induced R&D, including the grant and the effect on private R&D expenditures. Basically both types of R&D are equally productive in terms of the generation of products and services new to the market. In addition, subsidy-based R&D is used equally efficiently by first time and frequent participants for generating innovative output. For the statement that a rather stable pattern of program participation leads to a lower effectiveness of the instrument no evidence has been found.

Das Wichtigste in Kürze (Summary in German)

In den meisten OECD-Ländern werden die Forschungsaktivitäten der Unternehmen durch den Staat gefördert. Dabei bedienen sich die Länder verschiedener Instrumente, die von Zuschüssen für konkrete FuE-Projekte über steuerliche FuE-Anreize bis zu vergünstigten Darlehen reichen. Ziel ist es, die FuE-Anstrengungen der Wirtschaft zu erhöhen, um so die Innovationskraft zu stärken. In Deutschland nimmt die direkte FuE-Projektförderung (DPF) die dominierende Rolle innerhalb der staatlichen finanziellen Förderung von FuE ein. In dieser Studie werden die Effekte der DPF auf den FuE-Input und -Output von Unternehmen empirisch untersucht. Eine Erhöhnung der FuE-Ausgaben muss nicht zwangsläufig zu mehr Output führen, z.B. aufgrund der Durchführung von risikoreicheren Projekten oder steigender Löhne der FuE-Mitarbeiter.

Es wurde in einer früheren Untersuchung der DPF gezeigt, dass die Beteiligung von Unternehmen an dieser Förderung zu einem erheblichen Maße kontinuierlich über die Zeit erfolgt. Die sich daraus ergebende Frage ist, ob diese stabile Teilnahme Auswirkungen auf die Effektivität des Instruments hat. Des Weiteren hat eine Analyse für Irland gezeigt, dass die Wirkung der Förderung auf die FuE-Ausgaben mit der Höhe der Fördermittel variiert. In der vorliegenden Untersuchung wird daher berücksichtigt, dass die Effekte möglicherweise durch zwei Faktoren beeinflusst werden: die Teilnahmehistorie des Unternehmens an der Förderung und die Höhe des Zuschusses.

Die empirische Analyse basiert auf dem Mannheimer Innovationspanel, das eine jährliche Unternehmensumfrage zum Innovationsverhalten der deutschen Wirtschaft ist. Diese Daten wurden mit Informationen über die innerhalb der DPF geförderten Projekten angereichert. Der Datensatz besteht aus 8.500 Beobachtungen aus den Jahren 1994 bis 2005, die sowohl das verarbeitende Gewerbe als auch die wissensintensiven Dienstleistungen einschließen.

Insgesamt wird ein positiver Effekt von öffentlichen Zuschüssen auf die unternehmensfinanzierten FuE-Aufwendungen als Maß für den FuE-Input festgestellt. Jedoch weist nicht jeder Zuschuss die gleiche Wirkung auf. Die Ergebnisse zeigen, dass der Effekt (zumindest) mit der Unternehmenserfahrung hinsichtlich der DPF und der Höhe des Zuschusses variiert. Der Zuschuss sollte eine Mindestgröße aufweisen um einen signifikante Erhöhung der FuE-Aufwendungen zu bewirken. Außerdem steigt der positive Effekt mit dem regelmäßigen Erhalt der Förderung. Für die Untersuchung der Effekte auf den FuE-Output werden die FuE-Aufwendungen in zwei Komponenten aufgeteilt: (i) FuE-Aufwendungen, die auch ohne Förderung getätigt worden wären, und (ii) durch die Förderung induzierten FuE-Aufwendungen, d.h. der Förderbetrag plus die zusätzlich aufgewendete eigenfinanzierte FuE. Es zeigt sich insgesamt, dass beide Teile gleich effektiv hinsichtlich der Generierung und des Umsatzanteils von Marktneuheiten sind. Damit trägt die Förderung tatsächlich zur Steigerung der Innovationskraft bei. Außerdem werden die FuE-Aufwendungen, die der Förderung zugeschrieben werden können, gleich produktiv von Ersttteilnehmen und regelmäßigen Teilnehmern an der DPF eingesetzt. Die Ergebnisse geben somit keine Anzeichen dafür, dass die regelmäßige Teilnahme von Unternehmen an der DPF eine negative Auswirkung auf die Effektivität des Instrumentes hätte.

The Effect of Subsidies on R&D Investment and Success – Do Subsidy History and Size Matter?

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Abstract

This study provides insights into the effects of public R&D grants on R&D input and output of firms from Germany. Previous research has shown that the allocation of R&D project grants is rather stable regarding the pool of beneficiaries. The question is whether this participation pattern can be justified by its realized effects. In addition, the impact of the grant size on the effects is investigated. Therefore, I allow to a certain extent for heterogeneous treatment effects in these two dimensions. Using a sample of about 8,500 observations, a non-parametric matching approach with multiple treatments is applied to estimate the effects of public R&D grants on firm's R&D input. The results show that particularly frequently given grants as well as medium and large grants are suitable to increase the scope of firm-financed R&D plans. For the analysis of the effects on firm's R&D output the R&D expenditures are disentangled in R&D which would have been spent in the absence of the grant and publicly induced R&D, including the grant and the effect on private R&D expenditures. Basically both types of R&D are equally productive in terms of innovative output. For the statement that a rather stable pattern of program participation leads to a lower effectiveness of the instrument no evidence has been found.

Keywords: R&D, Public Subsidies, Innovative Performance, Germany

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1 Introduction

Investing in R&D is of great importance for the innovative potential and competitiveness of a knowledge-based economy. However, the public good characteristics of R&D lead to positive external effects because knowledge cannot be completely appropriated by the R&D conducting firm and thus leaks to other firms who increases the social returns but reduces private returns. Thus the incentives for companies to conduct R&D on a level that would be desirable from a welfare point of view are too low (Arrow, 1962). A second reason for underinvestment in R&D is related to imperfect capital markets. Due to the inherent high level of uncertainty in R&D and asymmetric information between inventors and investors it might be difficult or costly for firms to finance R&D with external capital (Hall, 2002).

Therefore, governments take action and employ different instruments to support private R&D activities, for example, via R&D grants, tax-based R&D incentives, or low interest loans. The most important tool used by the German government to fund R&D in private businesses is the so-called *D*irect R&D *P*roject *F*unding (DPF). The objective of this scheme is to increase a firm's R&D activities and to foster innovation in a number of pre-selected technology areas virtually covering all the main areas of modern technology (see, for example, BT-Drs., 1984; BMBF, 2004). The grants are awarded to R&D projects on a cost-sharing basis. Firms have to submit project proposals which are evaluated by the program managers with respect to their compliance with funding principles and eligibility criteria, including the level of technological advance and innovation potential. Up to 50 percent of the project costs are covered by the government. Thus, the funding directly reduces firms' R&D costs.

The challenge for the government is to select those projects which the firms would not have conducted without the grant. Based on the market failure arguments justifying the subsidies, as mentioned before, this means, more precisely, that the government needs to choose projects for which the private returns are too low and/or for which the financing cannot be realized otherwise. Since private returns as well as firm's financing opportunities for a project – and thus the conduct of the project in the absence of the grant – are difficult to assess for the government, the risk of allocation failure exists. However, if the agency is able to identify these projects a stimulation effect is likely.

Since private firms follow a profit-maximizing strategy, applying for a grant is attractive for the firms as long as application costs are low and the probability of receiving funding is high compared to alternative financing sources. On one hand the grant turns an unprofitable project in a profitable one or the money closes the funding gap for the project so that additional R&D activities can be undertaken by the firm. On the other hand the grant is seen as cheap money and taken to finance a project which would have also been conducted without public support. In this case the grant substitutes private for public R&D expenditures.

This paper contributes to the discussion of the effects and effectiveness of DPF as an innovation policy instrument by empirically analyzing the impact of DPF grants on firm's

R&D input but also on R&D output. The performance of the scheme is also important in the light of the goals for the EU set at the Lisbon and Barcelona European Councils which are, becoming the most competitive and dynamic knowledge-based economy in the world and increasing R&D spending to 3% of GDP by 2010, two-thirds of which should be funded by the private sector (Commission of the European Communities, 2000, 2002).

In the analysis I allow for heterogeneous effects in two dimensions: firm's DPF history and DPF grant size. Prior analysis of the DPF scheme reveals that the subsidization of firms via this instrument shows a certain level of continuity. The stability within the support scheme can be due to different reasons, like learning effects of prior participants, or the 'needy' projects being submitted by the same firms. On the other hand it is also conceivable that a long experience with public funding leads to a different behavior of the firm so that in particular frequent recipients take advantage of the grants and substitute otherwise self-financed R&D by them. The question is whether the rather stable participation pattern has an impact on the effectiveness of the scheme. The government needs to select those projects which the firms would not have conducted without the grant. If some of these projects are conducted by the same firms over time it does not necessarily lead to a failure of the scheme. I cannot identify the specific reasons why the support scheme is rather stable in Germany in terms of its recipients. However, the aim of the paper is to investigate whether a firm's subsidy history influences the effectiveness of the subsidies, i.e. whether this high level of continuity can be justified by its realized effects. A second focus is set on the role of the grant size in terms of the effects. Previous research by Görg and Strobl (2007) shows that the effects of grants on R&D input vary by the size of the grant. More precisely, the effects decrease by grant size. This relationship is analyzed for the DPF grants in Germany. In addition, the effects on R&D output are examined to verify whether the public money is translated successfully into new products.

The empirical analysis is based on an annual innovation survey, the German part of the Community Innovation Survey (CIS). This data is merged with a database comprising of information on subsidized projects in order to identify a firm's subsidy status for each year. The sample consists of over 8,000 firm-year observations covering the manufacturing and knowledge-intensive service sectors in the time period from 1994 to 2005. A non-parametric matching approach with multiple treatments is employed in order to provide insights into the impact of R&D grants on R&D input, viz. private R&D expenditures and on R&D output viz. sales with products new to the market. Thereby, I distinguish the effect with respect to firm's DPF history and DPF grant size.

The contribution of this study to the literature lies firstly in the allowance to a certain extent for heterogeneous effects of the subsidies. There is no study to date which links the effects of subsidies to firm's subsidy history by differentiating the effects between firms who receive an R&D grant for the first time or rather continuously. Another distinctive feature is that I condition the effects on the grant size – which has only been conducted in detail for Ireland. Finally, I extend the literature by examining the effects on R&D output.

The paper is organized as follows. In the next section the relevant literature is reviewed. Section 3 sketches the analyzed public funding scheme and derives the hypotheses. Subsequently the data set as well as the econometric approach underlying the empirical analysis is explained. The estimation results are presented in section 5, before drawing conclusions in the last section.

2 Literature Review

A large number of studies have been conducted over the last decades which try to answer the question of whether public R&D subsidies and company-financed R&D are substitutes or complements. Klette et al. (2000) and David et al. (2000) criticize, in their surveys, the underlying assumption of the random allocation of subsidies to firms in most analyses. This is indeed a challenging assumption since not all eligible firms might be aware of and acquainted with public support programs and therefore not all eligible firms apply for subsidies (self-selection). In addition, government authorities who decide on the applications may follow a picking-the-winner strategy in order to increase the probability of success and thus favor more capable or R&D-experienced firms. This leads to a selection bias which needs to be taken into account in order to analyze the question appropriately. Various studies have emerged since then which correct for the potential bias within the analysis of the effects of public R&D subsidies on firms' R&D activities.

With regard to studies for other countries or regions the results are somewhat ambiguous but tend to reject the full crowding-out hypothesis for R&D inputs.[1] Concerning empirical analyses for Germany all the studies agree on the rejection of the full crowding-out hypothesis. These include the analyses by Czarnitzki et al. (2007) and Aerts and Schmidt (2008) which are part of country comparisons with Finland and Flanders respectively, as well as studies on subsets of firms like studies by Czarnitzki (2001), Fier (2002), Almus and Czarnitzki (2003), Licht and Stadler (2003), Czarnitzki and Hussinger (2004), and Hussinger (2008) for the manufacturing sector, Czarnitzki and Fier (2002) for the service sector, Czarnitzki (2001), Almus and Czarnitzki (2003) and Czarnitzki and Licht (2006) for Eastern Germany.

The majority of the studies look at the overall receipt of a subsidy, irrespective of whether it is from the regional, federal or EU government and ignoring the size of the subsidy. Studies by Fier (2002), Licht and Stadler (2003), Czarnitzki and Hussinger (2004) and Hussinger (2008) focus on the DPF scheme and take the amount of the grant into account in order to be able to

[1] Full crowding-out effects are rejected in studies Aerts and Czarnitzki (2004, 2006), Aerts and Schmidt (2008) for Flanders, Duguet (2004) for France, González et al. (2005), González and Pazó (2008), Herrera and Heijs (2007) for Spain, Görg and Strobl (2007) for Ireland, Hyytinen and Toivanen (2005) for Finland, Lööf and Heshmati (2007) for Sweden, Streicher et al. (2004) for Austria. Partial crowding-out effects cannot not be rejected by Busom (2000) for 30% of firms (even full crowding-out effects are not ruled out), Herrera and Heijs (2007) for Spain, Kaiser (2006) for Denmark, Lach (2002) for Israel, Suetens (2002) for Flanders, Wallsten (2000) for USA while it is rejected by Aerts and Czarnitzki (2006) for Flanders and González and Pazó (2008) for Spain. For a review of recent studies see also Aerts et al. (2007).

distinguish between full and partial crowding-out and additionality effects. All the studies are based on the same data set: a sample of firms in the manufacturing sector covering the period 1992 to 2000 (1992-1998 in Fier, 2002). The cross-sections are pooled for the analysis. Fier (2002), Licht and Stadler (2003) and Czarnitzki and Hussinger (2004) apply a matching approach to investigate the effects of DPF grants on firm's R&D expenditures and/or R&D intensities. Hussinger (2008) employs parametric and semi-parametric selection models. In the four studies both full and partial crowding-out effects are rejected and they agree on the stimulation of firm's private R&D by DPF grants.

Most existing studies focus on the average effect of the subsidies for the firms. But some studies suggest that the effects might vary considerably. Busom (2000) points in her study to the variation of the effects – for the majority of the participants public funding induces private efforts, but for 30 percent of them full crowding-out effects cannot be ruled out – , but does not provide suggestions for the source of heterogeneity. A few analyses have taken a more detailed look at the effects and find heterogeneous effects depending on the type of recipient and subsidy characteristics.

González et al. (2005), González and Pazó (2008) and Lach (2002) find evidence that the subsidy effect varies by firm size. For Israeli manufacturing firms, Lach (2000) finds positive treatment effects on company-financed R&D expenditure for small firms (up to 100 employees) but no significant effects for large firms. For Spanish manufacturing firms, González and Pazó (2008) examine the effect of R&D subsidies on subsidized firms, depending on firms' size and the technological level of the sectors in which the firms operate. Their results suggest the absence of both complete and partial crowding-out effects between public and private R&D spending for any subsample of firms. But also no stimulation effect is found if the control group consists of only R&D performing firms. Allowing all firms as potential control firms they find a significantly positive effect on private R&D efforts which can be attributed to the group of small firms (up to 200 employees) and firms operating in the low technology sector. They explain this with the effect of subsidies on the induction to perform R&D activities for these firms. Both studies agree that, in particular, small firms tend to be stimulated by grants.

Empirical results which hint at a variation of effects by the subsidy size are found by Görg and Strobl (2007). They differentiate the effects on Irish manufacturing firms by the size of the subsidy. For this purpose they divide the firms into tertiles depending on the absolute volume of subsidies they receive. Estimating the effects of the subsidies for each group separately they show that small grants have an additionality effect for domestic firms whereas large grants crowd out firms' own R&D expenditures. For foreign firms neither additionality nor crowding-out effects are revealed for any subgroup.

The differentiation of effects which has been done so far for Germany involves firms' location and grant size. Czarnitzki and Licht (2006) find stimulating effects of public R&D subsidies on R&D and innovation expenditures for firms located in Eastern and Western Germany. However, the degree of additionality is larger for firms in the Eastern part. Fier (2002) differentiates the effects of DPF grants on firms' total R&D expenditure – including the volume of the DPF grant – among four classes of grant size and finds larger effects for larger grants. But this could also be solely due to the grant size. No further elaboration has been conducted on this issue.

In some studies the results of the direct effects on R&D input are used to investigate their further effect on the R&D output. Empirical evidence on this indirect impact is still limited. The indirect effects of R&D subsidies on patents as an R&D output measure are analyzed by Czarnitzki and Hussinger (2004), Czarnitzki and Licht (2006) and Aerts (2008). Hussinger (2008) and Aerts (2008) look at the effects on new products. Except for the study by Aerts (2008), the R&D outcome in the other studies is measured contemporaneous to the conducted R&D and the receipt of the funding. Overall the studies conducted for Germany agree on private and publicly induced R&D being equally effective in producing the different R&D outcomes.

In this paper I want to shed more light on the heterogeneity of the effects of subsidies. In doing so, I examine the role of firms' subsidy history for the relationship between public and private R&D expenditures, an aspect which has not yet been really explored. Hussinger (2008) has, however, addressed this issue and left it as an open question. Secondly, I elaborate further on the link between grant size and its impact on the effect. In addition, the effects of the subsidies on subsequent R&D output are examined, also depending on DPF history and size.

3 Contextual Framework

3.1 The Direct R&D Project Funding (DPF) Scheme

The focus in this paper is set on a specific public support scheme, the German Federal Government's non-defense DPF. This is the most important tool used by the German Federal government to fund R&D in private businesses.[2] In 2005, firms received a total of 745 million euros under this scheme (BMBF, 2006a).[3] Since then the importance of this funding scheme in Germany has increased and will increase further since it is the main distribution channel for the new 'High-Tech Strategy' launched by the Federal Government (BMBF, 2006b).

The DPF scheme offers grant aid funding for R&D projects in predefined fields of technology, for example, biotechnology, sustainable development, information technology and materials research, but also covers production technologies, transport, health, energy, optical, aerospace technology, space and many more. The fields of technology are selected by the government and the financial support is thematically restricted to R&D projects targeting the respective field of technology. Within each technology field thematic programs are

[2] Tax-based R&D incentives are not available in Germany.
[3] 448.5 million euros were given by the Federal Ministry of Education and Research, 296.1 million euros by the Federal Ministry of Economics and Technology.

defined which include funding objectives and eligibility criteria. Programs run for several years and are made public through calls. The application for R&D projects to be funded has to be made within fixed dates. Companies and research institutions – or both together in a collaborative project – can submit project-based applications for funding. Program agencies authorized by the government and responsible for specific thematic areas decide on the application. The funding is granted on a cost-sharing basis. Up to 50 percent of the R&D project costs are covered by the government. On an average a project lasts for three years and the grants are paid in pre-defined yearly installments.

3.2 Firm's subsidy history

Prior analysis of the DPF scheme reveals that the subsidization of firms via the DPF instrument shows a certain amount of continuity (Aschhoff, 2008). This can be due to different reasons. On the application side, firms who participate continuously in the scheme might have information advantages and know the support opportunities better than non-participating firms and thus apply more often. These firms might also realize learning effects by using their experience for submitting further successful applications. Thus, because the costs for applications are lower for these firms they apply more often and their applications are better since they know which projects are best-suited and how to set up a successful application. Consequently on the approval side, their proposals might be selected more often, although the necessity of financial support is the same or even lower for these projects.[4] Another theory is that the government authority wants to maximize the success rate of the subsidized projects and follows a picking-the-winner strategy, i.e. projects of firms who show high R&D capabilities are selected. But promising projects could also find other external investors so that a substitution effect is more likely. The stable pattern could also be a result of the fact that the government complies with attempts of specific interest groups to privilege certain firms (Fier and Harhoff, 2002). In this situation the R&D stimulation effects intended by the DPF might not be achieved. Furthermore, the regular receipt of DPF grants might also change the behavior of the awardees. Firms who have received DPF grants for a longer period have experienced the benefits and might view DPF grants as a source of cheap money. Due to their experience with the grants they are acquainted with the inherent procedure and know what is expected from them. They might already expect getting the money again and include it in their R&D planning. This reasoning suggests that the risk of a crowding-out effect, i.e. firms (partially) substituting public R&D spending for private R&D spending, might be particularly pronounced for these firms.

The relatively continuous participation of the same firms can also be a 'natural' result of the search by the government to pick those projects which the firms would not have conducted without the grant. If some of these 'needy' projects are submitted by the same firms over time it does not lead to a failure of the scheme.

[4] The criteria for approving a project do not differ between firms that have already participated in the DPF scheme and firms who want to participate for the first time. In contrast, for example, within the SBIR program additional criteria apply to the evaluation of SBIR applications of firms who had received awards in the past.

I cannot directly identify the predominant reasons why the support scheme is rather stable in Germany in terms of its recipients. However, the aim of the paper is to evaluate whether the continuous support of (some) firms can be justified by the realized effects in terms of R&D input and innovation output. In order to investigate this issue I distinguish between firms with different subsidy histories in the analysis of the effects. I examine the effects of DPF grants on R&D inputs for continuously supported firms, i.e. whether DPF grants have a stimulating or crowding-out effect on these firms. In addition, I compare the effects with those of first-time participants as a benchmark case. First-time applicants cannot calculate with the approval of the application and thus, with the DPF grant. They may not be familiar enough with the procedure of the DPF system. Therefore, if there is a change of behavior due to continuous support, the effects should be different for these two groups of firms.

3.3 Grant size

The grant size might be another characteristic which has an impact on the effect of the public support. In particular for large projects the conducting firms might not be able or willing to bear the risk alone and to finance the project with only their own financial means – even in the presence of a positive net present value – or get the project externally financed (GIB, 2004). Thus, the conduct of the project might be dependent on the provision of public money. Based on this argument a stimulation effect is more likely for large projects than for small ones. Vice versa, small projects have a higher tendency to lead to a crowding-out effect than larger projects.

Another situation in which crowding-out effects can take place is when firm's R&D capacity cannot be extended at will in the short-run even if the firm gets public support for a project, i.e. R&D activities are inelastic to a certain degree. For instance, R&D capabilities of a firm might be restricted in terms of R&D personnel. A firm might not find enough adequate R&D personnel necessary for a large project or it might hesitate to extensively increase the overall R&D personnel in order to avoid long-term employment commitments. Thus a large project might not be conducted additionally; it is more likely that the R&D expenditures will be reallocated from another project to the subsidized project which results in the other project not being undertaken. Thus, the probability of crowding-out effects increases with grant size. This reasoning contradicts the former derived relation between grant size and effects.

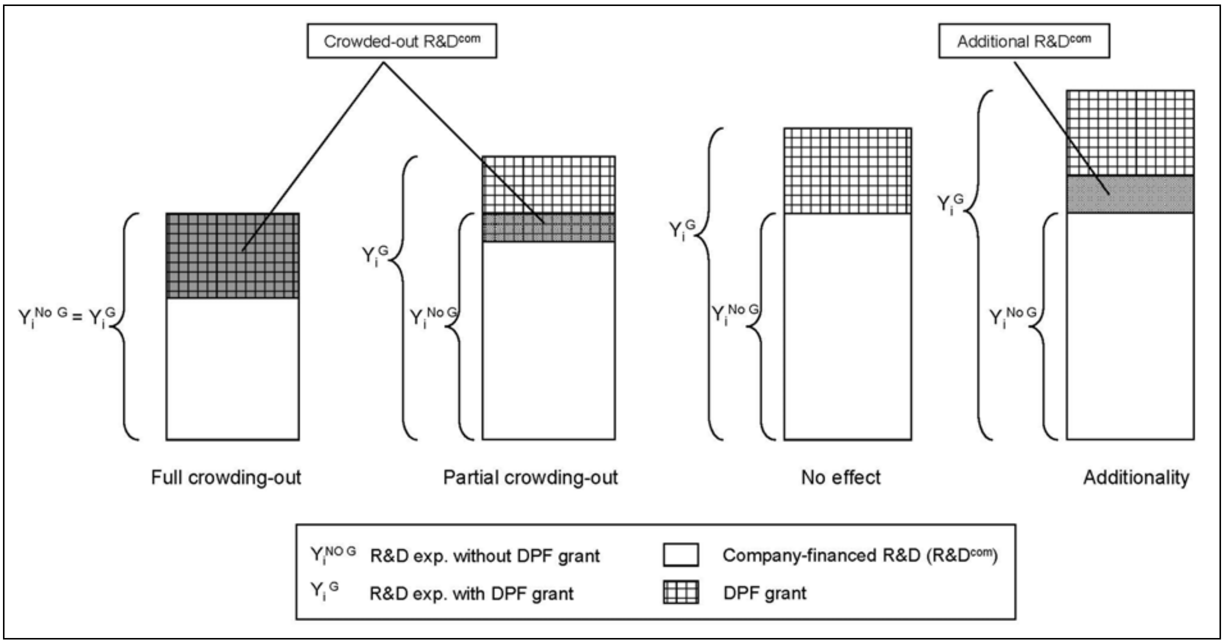
The direction of the impact of the grant size is a priori not clear. Görg and Strobl (2007) find evidence that effectiveness differs by grant size. They found for domestic firms in Ireland that the stimulating effect turns negative for large grants. With regard to foreign-owned companies the effect does not vary by grant size.

Positive effects on R&D input do not necessarily lead to new technologies. If the conduct of the project is only feasible due to the subsidies, the project probably has a low level of private returns or is associated with a high level of risk. In addition, the publicly induced R&D might not be spent very efficiently, for example, due to the higher demand for R&D personnel their wages increase as found by Goolsbee (1998) or Wolff and Reinthaler (2008). Therefore, the effects of DPF grants are also investigated in terms of R&D output depending on the different subgroups.

3.4 Taxonomy of possible effects on firm's R&D expenditures

Subsidies for R&D can have varying effects on a firm's R&D expenditure. The possible effects with the corresponding terminology used in the literature are sketched in this subsection. Beginning with the most negative effect, it is possible that the firm completely substitutes company-financed R&D by subsidies, i.e. the subsidy crowds out privately financed R&D Euro by Euro. In case of full crowding-out, a firm's total R&D expenditures are the same with and without subsidies. Partial crowding-out is found if privately-financed (total) R&D is lower (higher) in the situation of public funding than in the situation without it. However, the decrease is smaller than the amount of the grant. No effect of subsidies on firm's own R&D financing arises if the firm's privately-financed R&D expenditure is the same with and without subsidies. Public subsidies and privately-financed R&D act like complements. Firm's total R&D expenditures increase by the amount of the subsidy compared to the scenario in which the firm does not receive a subsidy. An additional effect of the subsidy is achieved if the firm increases privately-financed R&D spending due to the receipt of the subsidy, i.e. company-financed R&D is higher in the presence of a subsidy than if the firm does not receive a subsidy. The four possible types of effects are depicted in Figure 1.

Figure 1: Concept of possible effects of a DPF grant on firm's R&D expenditure



Source: Own illustration.

4 Empirical Specification

The methodological approach chosen to examine the change in firm's R&D input and output arising from DPF grants is outlined in the next subsection. In the subsequent subsections I describe the data set and variables used for the analysis.

4.1 Estimation strategy

4.1.1 Effect of DPF grants on R&D input

In the empirical analysis it needs to be taken into account that the receipt of a subsidy does not happen by chance but is rather subject to different selection processes, both on the firm's and the government's side. In the case of firms with per se higher R&D dynamics or a more efficient innovation management that transfers R&D results more successfully into innovations who show a higher propensity to receive funding, effects of public funding on R&D input and output need to be controlled for this selection bias. Several econometric methods have been developed in order to get reliable results on program effects even in the presence of selection bias. Such econometric techniques include instrumental variable (IV) regression, difference-in-difference analysis and matching methods.[5] The latter approach was established and first used in the evaluation of labor market economics (see, for example, Angrist 1998, Heckman et al. 1997, 1998a, 1998b, Lechner 1999, 2000) and has been later transferred to the evaluation of public R&D funding. The matching approach has been extended by Imbens (2000) and Lechner (2001) from the context of a binary treatment to the case of multiple treatments. It has been widely used in recent years as an estimation technique[6] and is also applied in this study.

In the first step the effect of DPF grants on firm's R&D expenditures is investigated. Since I am interested in the role of DPF history and DPF size, I define a discrete number of subgroups of DPF recipients according to these two dimensions and consider them as multiple treatments. Görg and Strobl (2007) chose the same approach in their study on grant size. In total there are $M+1$ mutually exclusive states or treatments due to M different categories plus the case in which the firm does not receive a DPF grant. Participation in a specific category is indicated by the variable $S \in \{0,1,...,M\}$. The R&D measures are the so-called outcome variables and the value is denoted by $\{Y^0, Y^1, \ldots, Y^M\}$. For each firm only the realization of the outcome variable in state $S=m$ is observable. The remaining M outcomes are not observed for the firm. The aim is the pairwise comparison of the effects of treatments m and l on the firms in state m, for example, comparing the outcome between first-time subsidized firms ($S=m$)

[5] For an overview and discussion of the econometric approaches see Heckman et al. (1999), Blundell and Costa Dias (2000) or Aerts et al. (2007). The latter survey concentrates on the evaluation of public R&D subsidies.

[6] Aerts and Czarnitzki (2004), Almus and Czarnitzki (2003), Czarnitzki (2001), Czarnitzki et al. (2007), Czarnitzki and Fier (2002), Czarnitzki and Hussinger (2004), Czarnitzki and Licht (2006), Fier (2002), Gonzáles and Pazó (2008), Herrera and Heijs (2007), Licht and Stadler (2003), Lööf and Heshmati (2007) apply nearest neighbor matching; Duguet (2004), Licht and Stadler (2003) kernel matching; Aerts and Schmidt (2008), Görg and Strobl (2007) a combination of matching and difference-in-difference. Czarnitzki et al. (2007) and Görg and Strolb (2007) consider multiple treatments in their studies.

and not subsidized firms ($S=l$) conditional on the first-time receipt m. The average treatment effect on the treated $\alpha^{m,l}$ can be expressed as

$$\alpha^{m,l} = E\left(Y^m \mid S=m\right) - E\left(Y^l \mid S=m\right). \tag{0.1}$$

Since Y^m is observed, $E(Y^m \mid S=m)$ can be measured directly by the sample mean of the outcome for the group of firms with $S=m$. The situation $E(Y^l \mid S=m)$ is called the counterfactual situation since it is not observable by design and has to be estimated. In the presence of a selection bias an estimation of the counterfactual outcome via the sample mean of the outcome for the group of firms with $S=l$ leads to biased results.

The basic idea of matching is to balance the sample of firms receiving m and firms in state l by selecting the best twin (in terms of exogenous characteristics that determine the state m) from the control group for each firm in state m. Then the means of the outcome can be compared between the two groups. The advantage of the matching method is – since it is a non-parametric method – that a functional form for the outcome equation is not necessary. The disadvantage is the need for strong assumptions. In order to identify the average treatment effect three assumptions have to hold: the conditional independence assumption (CIA), the stable unit treatment value assumption (SUTVA) and the common support. The CIA was introduced by Rubin (1977) and states that for firms with the same set of exogenous characteristics $X = x$, the treatment and outcome variables are independent:

$$Y^0, Y^1, \ldots, Y^M \perp S \mid X = x. \tag{0.2}$$

The CIA implies that all characteristics which influence both treatment and potential outcome have to be observed. It cannot be tested whether the CIA is fulfilled or not. Given the broad range of variables in our data set it is reasonable that I have enough information on the firms to sufficiently approximate the treatment and the outcome so that the CIA holds. This is supported by the fact that comparable data sets have been used in the past for several matching studies (see footnote 6). If the CIA holds, the outcome of the treated group – firms in state m – in the counterfactual situation can be approximated by the outcome of a control group of firms in state l which strongly resembles (i.e. match) the treatment group:

$$E\left(Y^l \mid S=m\right) = \underset{P^m(X),P^l(X)}{E}\left\{E\left[Y^l \mid P^m(X), P^l(X), S=l\right] \mid S=m\right\}. \tag{0.3}$$

In addition, the SUTVA demands that the treatment of a particular firm must not influence the outcome of other firms (Rubin, 1990). The validity of SUTVA cannot be tested empirically either. A further requirement is the common support which requires that firms with the same characteristics have a positive probability of participating in all states. This condition assures that for each treated observation a similar control can be found. In order to secure common support, observations with probabilities larger than the smallest maximum and smaller than the largest minimum of all subsamples defined by S are deleted.

If all assumptions hold the average treatment effect of the treated firms can be estimated as

$$\alpha^{m,l} = E\left(Y^m \,|\, S = m\right) - \underset{P^m(X),P^l(X)}{E}\left\{E\left[Y^l \,|\, P^m(X), P^l(X), S = l\right] | S = m\right\}. \tag{0.4}$$

Differences in the means of the outcome variable between firms receiving treatment *m* and the selected control group consisting of firms in state *l* are then attributed to the treatment *m*, i.e. to the first-time receipt of a DPF grant in the example above (Heckman et al. 1997).

In the ideal case, the best twin for a firm in state *m* is the firm which is identical in all relevant characteristics *X*. But if the number of matching criteria is large it would hardly be possible to find any such observations. Therefore, Rosenbaum and Rubin (1983) developed propensity score matching. The idea is to estimate the propensity score which is the probability of being treated with *m* and to find pairs for each firm receiving *m* in the group of firms in state *l* that have the same probability value of treatment *m*. Usually one does not perform an exact matching but the popular 'nearest neighbor' matching which is also applied in this study, i.e. one selects the control observation with the estimated probability value closest to the treated firm. Using this propensity score one reduces the multidimensional problem of several matching criteria to one single measure of distance. Lechner (1998) introduced a modification of the propensity score matching, as one often wants to insert additional variables, for example, firm size, into the matching function. In this case instead of a single *Z* (propensity score) other important characteristics of the firms may also be employed in *Z*.

The selection of the control firm is based on the Mahalanobis metric. In order to identify the firm in state *l* which is the closest neighbor to the treated firm in state *m*, the distance to minimize is

$$MD_{ml} = \left(z_m - z_l\right)' \Omega^{-1} \left(z_m - z_l\right) \tag{0.5}$$

with Ω^{-1} being the sample covariance matrix of the comparison group.

In order to examine the effect in terms of firm's DPF history, I consider three treatments: no DPF, first-time DPF and frequent DPF. The analysis with respect to DPF size is based on four treatments: no DPF, small DPF, medium DPF, and large DPF. The corresponding propensity scores are estimated on the basis of a multinomial probit model including several firm characteristics – which are explained in the subsection on the variables – to explain the treatments. In addition to the propensity score, I include the firm size (no. of employees in logarithm), and the knowledge within the firm (patent stock) in the calculation of the Mahalanobis distance since both these quantitative information are of particular importance for the explanation of receiving a DPF grant and R&D spending. Besides the receipt of other subsidies (from EU and from regional government) and the year need to be exact matches to avoid biases as far as possible due to other funding sources and changes in macroeconomic conditions over time. The matching protocol follows the one by Gerfin and Lechner (2002) which is also applied by Czarnitzki et al. (2007) and is depicted in Table 8 in the appendix.

4.1.2 *Effect of DPF grants on R&D output*

In order to analyze the effect of the subsidies on R&D output I apply the approach suggested by Czarnitzki and Hussinger (2004). Based on matching results, R&D expenditures of subsidized firms are disentangled into two components: R&D expenditures which would have been spent anyway (R&D_C), i.e., also without the subsidy, and the publicly induced R&D which encompasses the amount of R&D grant and the additionally invested amount (R&D_Dif). For not subsidized firms the former R&D part equals the observed R&D expenditures, the latter R&D measure is zero by construction. In order to relate these two measures of R&D input to output, 'productivity functions' are estimated. Firms' innovation output is measured in terms of sales with market novelties and the corresponding share of sales. In addition to the R&D input measures, I control for firm's sales to proxy firm's access to the market, previous successful R&D with means of the lagged patent stock, whether the firm cooperates with other firms or institutions in its innovation activities and whether the firm is located in Eastern Germany. In addition, industry and year dummy variables are included in order to take industry differences and macroeconomic variation into account. The control variables are included in vector $V_{i,t}$. Thus, the estimated equation has the following form:

$$Output_{i,t+j} = f(\mathrm{R\&D\_C}_{i,t}, \mathrm{R\&D\_Dif}_{i,t}, V_{i,t(t-1)}), \qquad (0.6)$$

with j=1,2. To investigate the effect on the level of sales with market novelties, I take the logarithms of the variable. Zero values are set to the minimum value. Since the level of innovative sales is left-censored and the intensity left- and right-censored (at 0 and 100 respectively) I apply censored regression models for these models.

4.2 Data Set

The empirical analysis is based on the Mannheim Innovation Panel (MIP), an annual innovation survey conducted by the Centre for European Economic Research (ZEW) on behalf of the BMBF since 1993.[7] The MIP is the German part of the European-wide harmonized Community Innovation Survey (CIS). The data contains information on firm's R&D and innovation activities and a wide range of firm characteristics like number of employees, sales and industry among other things. I use the surveys conducted between 1995 and 2006 covering the time period 1994 to 2005. Since participation in the survey is not mandatory half of the firms are only observed once. Thus, the different cross sections are pooled for the empirical part. The survey data is supplemented with information on the DPF grants which is extracted from the R&D project database of the German Federal Government. The project-level data on the grants is aggregated to the firm level and is used to identify the years in which a firm received a grant within the DPF scheme. In addition, patent application data from the European Patent Office is merged.

[7] For a detailed description of this database see Rammer et al. (2005).

Since the DPF scheme does not aim at motivating firms to start R&D activities – this has also been shown empirically (cf. Aschhoff, 2008) – the sample of firms is limited to R&D-performing firms, i.e. firms with positive R&D expenditures. This restriction ensures that the potential control group – firms without DPF grants – is more similar to firms with DPF grants and avoids an overestimation of the effect. The final data set contains 8,528 firm-year observations from 3,583 different firms from manufacturing and knowledge-intensive service sectors.

4.3 Variables

4.3.1 Endogenous variables

In this study I empirically analyze the effects of DPF grants on firm's R&D activities in Germany. In total I have three endogenous variables: the treatments, i.e. the receipt of DPF grants, firm's R&D expenditure as outcome variable in the matching and sales with products new to the market as a measure for R&D output.

Since it is assumed that the DPF grants are not allocated randomly we treat the receipt of a DPF grant as endogenous. Almost 13 percent of the firms in the sample receive DPF grants amounting to 146,000 euros on average.[8] I want to allow, to a certain extent, for heterogeneous treatment effects for firm's DPF history and DPF size. Therefore I split the sample of DPF recipients into several subsamples. In terms of firm's DPF history I am particularly interested in the effects due to frequent support. Therefore, one subgroup contains firms who continuously received DPF grants over a 5 year period (*frequent DPF*).[9] A second group which serves as a benchmark group for the effects consists of firms who receive DPF grants for the first time in the current or preceding year within the last 5-year-period. Thus, these firms get new grants and they do not have (recent) experience with the scheme. The rest of the funded firms, i.e. firms who receive DPF grants occasionally, are not considered in this part of the analysis.

Alternatively I divide the firms who receive DPF grants into three subgroups depending on the amount of the DPF grant(s) based on tertiles of the subsidy size. Small grants are below 37,200 euros, large ones larger than 99,000 euros. Since the data set includes observations from a 12-year-period all monetary variables have been deflated.[10]

My interest lies in the effects of the subsidies on firms' R&D expenditure. In order to test the full and partial crowding-out hypothesis I use the following outcome variables: (i) *total R&D* expenditures[11] (in million euros), and (ii) *private R&D* expenditure which includes only

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[8] In 2000 and from 2002 onwards, firms with DPF grants are deliberately overrepresented in the sample. Without these additional firms the share of firms receiving DPF is 10%. Results are robust to the drop of these firms.

[9] The grant is not necessarily newly awarded. A grant in a certain year can also refer to an ongoing subsidized project.

[10] The industry-specific deflator is developed by Peters et al. (2009) and takes into account the composition of R&D expenditures in terms of investments, personnel and material expenditures. The deflator consists of the respective indices, weighted by their shares in the industry.

[11] Defined in accordance with the Frascati Manual (OECD, 1993)

privately financed R&D expenditures, i.e. total R&D minus the amount of DPF grants. Private R&D expenditures may also include subsidies awarded under other schemes or by other authorities. Since I do not have information on the amount of this support, I cannot adjust the private R&D spending. However, in the matching approach I control for other support measures by ensuring that this subsidy status is identical for firms with DPF and their matched counterparts. As a robustness check the corresponding intensities defined as the R&D variables divided by sales (multiplied by 100) are also considered. In Table 1 R&D spending for the different treatment groups are presented. Due to the skewed distribution, the R&D variables are included as logarithms in the analysis.

Table 1: Mean values of R&D expenditures

	Total R&D°	Private R&D°	Total R&D/sales^{+}	Private R&D/sales^{+}	No. of obs.
whole sample	1.660	1.641	6.645	6.327	8,528
no DPF	1.211	1.211	5.738	5.738	7,405
with DPF	4.618	4.472	12.624	10.211	1,123
with DPF					
DPF history					
first	2.603	2.508	12.154	9.612	333
frequent	6.341	6.131	13.406	11.102	370
DPF size					
small	2.429	2.411	8.728	7.731	374
medium	3.323	3.260	12.908	10.365	374
large	8.091	7.737	16.225	12.529	375

Note: ° in million euros, deflated. $^{+}$ in percent. Sample is restricted to firms with positive R&D expenditures.

Firms who receive DPF grants show higher R&D expenditures than non-funded firms, both in terms of absolute values and intensities. The same picture emerges when subtracting the volume of the grant from the overall R&D expenditure. Firms receiving DPF grants spend, on average, almost four times more on R&D than R&D performing firms without DPF grants. Relating the expenditures to firm's sales, the difference is not as large but still significant. When firms are distinguished by their DPF history, it becomes apparent that frequent DPF recipients have higher R&D spending than first-time recipients. However, R&D intensities are not significantly different. The higher absolute values of the frequent recipients are due to the fact that this group consists of larger firms in terms of their sales. The descriptive comparison gives no indication that the effect on R&D depends on DPF history, once it is controlled for firm size. Firm's private R&D spending increases with the amount of the R&D grant. Firms receiving a large DPF grant – the median amount is 200,000 Euro – spend significantly more on R&D with their own financial means than firms who receive smaller DPF grants. In terms of R&D intensities firms with middle- and large-sized grants have a higher intensity than small grant recipients. This indicates that the effect of DPF funding might increase with grant size.

Firms' R&D output is measured by the sales with market novelties (logarithm values are taken in the estimations) and the corresponding share in total sales. These variables not only capture the generation of new products but also their market success. Since the development of new products takes time the variables refer to subsequent periods with respect to the R&D

investments. This information is taken from subsequent survey years. Since not all firms participate in the survey each year, I can only use a little less than half of the observations for this analysis. About 48 percent of the firms don't have any sales with market novelties. Less than 1 percent of the firms realize 100 percent of the sales with new products to the market. The summary statistics of the output are presented in Table 2.

Table 2: Summary statistics of R&D output

	Mean	Std. Dev.	Min	Max	No. of obs.
Sales with market novelties °					
t+1	2.570	7.501	0	71.102	3,951
t+2	2.464	7.253	0	71.849	3,544
Share of sales with market novelties $^{+}$					
t+1	8.217	15.550	0	100	3,951
t+*2*	7.738	14.467	0	100	3,544

Note: ° in million euros, deflated. $^{+}$ in percent.

4.3.2 Explanatory variables

The explanatory variables include variables which may influence the probability of receiving a DPF grant and R&D expenditure. The variables are similar to those found important in previous empirical studies. First of all I control by means of dummy variables for the receipt of subsidies from European schemes within the preceding three-year-period *t-2* to *t* (*Sub_EU*) and the receipt of subsidies from the regional level within this period (*Sub_regional*). Firms who participate in other funding programs probably know the subsidy system with its funding opportunities quite well and have expertise in applying for and getting public grants. Therefore they are also more likely to receive a DPF grant. Dropping all firms receiving subsidies from other sources leads to a reduction of the DPF recipients by 50 percent and may cause a severe bias in the sample of DPF recipients. Instead within the matching procedure the statuses of the two other funding sources are included in the matching function as an exact matching condition, i.e. they are identical for treated and selected control firms. As a robustness check the analysis will be repeated only with treated firms who receive no other subsidies.

Firm size is expected to be an important variable in explaining the receipt of DPF grants and the R&D activities (e.g., Hussinger 2008, Griffith et al., 2006). R&D projects conducted by SMEs can receive grants up to 60 percent of the project costs (instead of 50 percent). Firm size is measured as the number of employees and taken as a logarithm to avoid estimation biases caused by its skewed distribution. In addition, firm's age is controlled for also as a logarithm.

I use three variables to control for firm's R&D capabilities. R&D capable firms are both more likely to get DPF grants and probably spend more on R&D. The sample is restricted to firms with positive R&D expenditures but that does not exhibit information on whether a firm conducts R&D on a continuous basis. Therefore, a corresponding dummy variable is generated: *R&D_con*. Conducting R&D continuously is often associated with having a separate R&D department and separate R&D controlling which can ease to comply with accounting and project documentation requirements of the DPF scheme. A second measure for firms' capabilities to generate and acquire knowledge is related to the human capital. I proxy a firm's human capital intensity by the percentage of employees with a university degree (*Qualification*). Previous (successful) R&D activities are approximated by the firm's patent stock. This variable is generated by depreciating the sum of all patent applications which were filed at the European Patent Office since 1979 until *t-1*. The depreciation rate is constant and equals 0.15 which is common in the literature (e.g. Griliches and Mairesse, 1984; Hall, 1990). Due to variations in the patent propensity between industries, the patent stock is rescaled by the average patent stock on the three-digit-level (*Patent_stock_dev*). To ensure that the patents refer to previous R&D activities the variable considers only patent applications till *t-1*.

Firms who are part of a national or foreign enterprise group will have access to a broader knowledge pool and might benefit from knowledge transfers within the group. Besides SMEs which belong to a group with a large parent company are not eligible anymore for DPF subprograms designed for SMEs. The DPF scheme might also be oriented in particular towards domestic firms since the government wants to generate economic effects located in Germany out of DPF funding. With respect to R&D activities, foreign firms may pool their activities in the parent's home country. Two dummy variables are included in the analysis indicating the membership in a national or foreign group (*Group_national*, *Group_foreign*).

Firms located in the Eastern part are still lagging behind firms from the Western part in terms of R&D and productivity (Czarnitzki, 2005; Aschhoff et al., 2008). I generate a dummy variable for firms located in Eastern Germany (*East*). Finally, sector and year dummy variables are included to control for further differences between industries and over time in the economy respectively. Summary statistics of all explanatory variables are provided in Table 9 in the appendix.

5 Empirical Results

5.1 Effect of DPF grants on R&D input

5.1.1 Input effects of DPF receipt

In the first step I examine the effect of DPF grants on R&D input. First, the effect of receiving a DPF grant in general is analyzed. A probit model on the probability of receiving a DPF grant is estimated (see Table 10 in the appendix). The results give evidence for the presence of a selection into the DPF scheme. In particular the participation in other funding schemes helps to get DPF grants. Additionally large firms with a strong R&D record are more likely to participate in the scheme since the probability increases with R&D capabilities, past patenting and firm size. This can be because of company decisions (i.e. applying more often or being more capable to submit high-quality proposals) or a picking-the-winner strategy by the government. Furthermore, the government sets a focus on high technology manufacturing firms. Since special R&D support programs for firms located in Eastern Germany are partly not integrated in the DPF scheme, East German firms do not receive DPF grants significantly more often. The results are in line with previous findings (e.g. Fier, 2002; Hussinger, 2008).

In the next step a "twin" firm is selected for each firm that has received a DPF grant ("treated firm"). The matching procedure is successful in balancing out the differences for the exogenous variables between the treated and the selected control group since t-tests on the mean difference of these variables do not show significant differences after matching.[12] Hence the remaining differences in the outcome variables, after the matching procedures between the treated and the non-treated firm, can be interpreted as the average treatment effect on the treated firms (α). Table 3 illustrates the values for the outcome variables, i.e. firm's R&D efforts for both groups and the corresponding differences. Looking at the total R&D expenditures and the R&D intensity, the average treatment effect is significant and positive, i.e. DPF firms spend more on R&D and show a higher R&D intensity than the group of matched control firms. Thus the full crowding-out hypothesis can be rejected. By looking at the private R&D efforts only – i.e. subtracting the DPF grant from total R&D – the effect is still positive and significant. Private R&D expenditures of firms with DPF grants are higher both in absolute and relative terms than that of firms without the grant. Thus, the DPF scheme stimulates additional private R&D spending.

The results confirm previous studies focusing on the DPF scheme which also find additionality effects for the period until 2000 (Fier, 2002; Licht and Stadler, 2003; Hussinger, 2008). It seems that in recent years this effect has not changed.

Table 3: Comparison of R&D efforts after the matching for the whole sample

	With DPF	No DPF	α
ln(total R&D)	6.907	6.337	0.571***
ln(total R&Dint)	1.664	1.200	0.464***
ln(private R&D)	6.729	6.337	0.392***
ln(private R&Dint)	1.486	1.200	0.286***
no. ob obs.	1,108	1,108	

Note: Mean values are shown. α is the average treatment effect of DPF on the treated firms. *** (**, *) indicates significance level of 1% (5%, 10%) of the two-sided t-tests on mean equality between the firms with DPF and the selected control group. The standard errors of the t-statistics are based on the approximation by Lechner (2001) that accounts for sampling with replacement in the selected control group. The control variables as well as the propensity score are not significantly different between the treated and selected control groups after matching. Sub_EU, Sub_regional and year variables are exact matches. To improve the readability by avoiding negative mean values, the logarithm is taken from R&D expenditures measured in 1,000 euros. α and its significance are not affected by this rescaling.

[12] Results of the t-tests are not reported. In order to evaluate the quality of the matching I also re-estimate the propensity score by using only the matched sample and taking account of replacement in the control group by weighting. As stated by Sianesi (2004) the pseudo-R2 after matching should be quite low because there should be no more systematic differences in the regressors between treated and control companies. In this setting the Pseudo-R2 after the re-estimation is below 0.005 and a likelihood ratio suggests that there is no joint significance of all covariates of the probit model after matching.

5.1.2 *Input effects depending on DPF history*

In the next step I analyze the effect of the subsidies depending on a firm's DPF history. For this purpose I generate two clear-cut subsamples of treated firms as described in section 4 – first-time DPF recipients and frequent recipients, both measures relate to the preceding five-year-period. The two types of recipients are regarded as two treatments. The sample of non-treated firms remains the same.[13] Multinomial probit models are estimated to determine the propensities to be either type of DPF recipient (see Table 10 in the appendix). It becomes apparent that in particular frequent DPF recipients are successful in raising other public funding and more prevalent in medium-high and high technology manufacturing sectors.

Based on the estimated propensity scores and after taking care of common support, the three groups – frequent DPF firms, first time DPF firms and firms without DPF are pairwise matched. The R&D efforts and their differences after matching are presented in Table 4. First I am interested in the effect for the two types of DPF recipients compared to non-recipients in order to conclude whether the grants have a stimulation effect on both groups. The effect on first-time recipients serves basically as a benchmark for the effect on the frequent ones. For each DPF group, total R&D is higher for supported firms than for their not supported counterparts, i.e. the hypothesis of full crowding-out can be rejected. In terms of private R&D expenditures an additionality effect is only proved for the frequent DPF recipients. For first-time DPF participants, no effect of the subsidy on private R&D is found. Though private R&D spending is higher for funded firms, the difference is not significant.[14] These results show that the DPF grants are spent in addition to private R&D so that partial crowding-out can be rejected as well. The results give no indication that the impact of DPF grants is lower on firms who frequently receive grants. In contrast, an additionality effect is found for this group and no significant effect is found for first-time participants. Furthermore, the group of frequent recipients is directly compared to the first-time participants. Since the number of observations is similar in both groups but the characteristics of the firms differ between the groups for a relatively large share of frequent participants, no comparable control firm could be found and was dropped.[15] This comparison also indicates that the effect of DPF grants on R&D spending is higher for frequent recipients.

[13] An alternative could be to calculate the effects for the two subgroups based on the results of the whole sample. An underlying assumption would be that the likelihood for both treatments is the same. Since the determinants between the two groups differ to some degree, as shown in the multinomial probit model, repeating the whole analysis for the two treatments provides more precise results.

[14] One may argue that the effect for the group of first-time recipients is not significant because the grants are, on average, much smaller than those for frequent recipients. However, since the first-time participants are also smaller in terms of their size and R&D expenditures, the relative contribution of a DPF grant to total R&D spending is comparable for both groups. The grant accounts for about 15% of the total R&D expenditures in both groups.

[15] Although this is typical in this kind of analysis, the results should be interpreted with some caution since a quarter of frequent recipients are not included in the comparison.

Table 4: Comparison of R&D efforts after the matching depending on firm's DPF history

	First DPF	No DPF	$\alpha^{m,l}$	Frequent DPF	No DPF	$\alpha^{m,l}$	Frequent DPF	First DPF	$\alpha^{m,l}$
	m	*l*		*m*	*l*		*m*	*l*	
ln(total R&D)	6.585	6.162	0.423***	7.318	6.654	0.664***			
ln(total R&Dint)	1.539	1.218	0.322***	1.902	1.369	0.533***			
ln(private R&D)	6.406	6.162	0.244	7.145	6.654	0.491***	7.157	6.766	0.391*
ln(private R&Dint)	1.361	1.218	0.143	1.729	1.369	0.359***	1.555	1.206	0.349**
no. ob obs.	320	320		340	340		264	264	

Note: Mean values are shown. $\alpha^{m,l}$ is the average treatment effect on the treated. *** (**, *) indicates significance level of 1% (5%, 10%) of the two-sided t-tests on mean equality between the treatment group *m* and the selected control group *l*. The standard errors of the t-statistics are based on the approximation by Lechner (2001) that accounts for sampling with replacement in the selected control group. The control variables as well as the propensity score are not significantly different between the treated and selected control groups after matching. Sub_EU, Sub_regional and year variables are exact matches. To improve the readability by avoiding negative mean values, the logarithm is taken from R&D expenditures measured in 1,000 Euro. $\alpha^{m,l}$ and its significance is not affected by this rescaling.

5.1.3 Input effects depending on DPF size

In order to analyze the effect depending on the grant size I divide the sample of DPF firms into three subgroups according to the received DPF amount and repeat the analysis. The dependent variable of the multinomial probit has four outcomes; namely, no DPF, small DPF, medium DPF and large DPF. The results reveal that the determinants are rather similar for the three groups (see Table 10 in the appendix). Firms with higher amounts of DPF support are a little bit larger and the financial support from the EU is more prevalent for them than for firms who receive small or medium-sized amounts. For the latter group of firms public funds from regional authorities are more likely. Again the groups are matched pairwise after common support is achieved. The resulting differences in the private R&D variables are shown in Table 5.

DPF grants do not displace private R&D investments in any of the three subgroups. No crowding-out of private R&D expenditures is found. For medium and large-sized grants a stimulation effect on private R&D expenditures is observed. These firms increase their private R&D spending due to the receipt of the grant. For firms with small grants this complementary effect is not significant. They spend the amount of the grant additionally on R&D but these grants do not induce a statistically significant supplementary amount of company-funded R&D expenditures. The results give evidence for the need of firms for public support to conduct additional R&D projects. In particular the findings support the financial constraint argument for larger projects. These results contradict the findings of Görg and Strobl (2007) who recorded an additionality effect for small grants and a crowding-out effect for large grants for their sample of Irish manufacturing firms.

Table 5: Average treatment effects on the treated depending on DPF size

	Comparison group l		
Treatment *m*	No DPF	Small DPF	Medium DPF
	Outcome variable: ln(private R&D)		
Small DPF	0.168		
Medium DPF	0.392***	0.219	
Large DPF	0.444***	0.776***	0.356**
	Outcome variable: ln(private R&Dint)		
Small DPF	0.156		
Medium DPF	0.250**	0.159	
Large DPF	0.276**	0.478***	0.115
	No. of matched pairs		
Small DPF	361		
Medium DPF	363	311	
Large DPF	345	286	306

Note: Average treatment effects on the treated ($\alpha^{m,l}$) are shown. *** (**, *) indicates significance level of 1% (5%, 10%) of the two-sided t-tests on mean equality between the treatment group m and the selected control group l. The standard errors of the t-statistics are based on the approximation by Lechner (2001) that accounts for sampling with replacement in the selected control group. All control variables as well as the propensity score are not significantly different between the two groups after matching. Sub_EU, Sub_regional and year variables are exact matches.

One may argue that the frequent DPF participants get the large projects and therefore the effect may be simply a size effect for them. But even in this case the results reject that in particular frequent DPF participants substitute private R&D spending by public support. Indeed half of the frequent participants receive large grants and about 19 percent small ones whereas the opposite applies to the first-time participants (46%/19% receive small/large grants). However, looking at large grants and calculating the effect for first-time and frequent recipients separately, it becomes apparent that the effect is larger for the latter group. This also holds if the focus is set on small grants. The other way round, concentrating on first-time recipients and calculating the effect for each size class, the effect for firms receiving a large grant is much larger than the effect of small grants. For frequent recipients the effects are more similar for different grant sizes. Splitting the sample into all possible combinations in terms of DPF history and size would lead to too few observations for each category in order to obtain reliable results for these subsamples.

5.1.4 Robustness check

Using propensity scores on the basis of multinomial probit model estimations may risk that if the equation for one alternative is misspecified all conditional probabilities could be misspecified. Thus, as a robustness check the effects are recalculated based on conditional probabilities which are estimated separately for each pair of subsidy category with the means of binary probit models (see appendix B). The effect of DPF grants on frequent recipients compared to first-time recipients is not that pronounced here. But overall, the results shown above are supported by this check.

The results might also be biased due to effects from the receipt of subsidies from other sources, like regional or European institutions. However, data on the amount of these subsidies is not available. In the analysis it is ensured that the corresponding subsidy statuses are identical between the matched pairs. Nevertheless the imposed assumptions are that these other subsidies have the same size and the same effect on the matched firms. To check whether the results are robust to these assumptions the analysis is repeated excluding those firms who received R&D subsidies from the EU or from regional authorities (see Appendix C). The significance of some effects dropped slightly in this restricted sample but the findings do not change qualitatively.

5.2 Effect of DPF grants on R&D output

In order to investigate the effects of receiving a DPF grant on a firm's R&D output (market novelties) the R&D expenditures are divided into two parts based on the results of the input analysis. The counterfactual R&D (R&D_C) is defined as the amount which would have been spent on R&D without having received the grant. The R&D which is related to DPF funding (R&D_Dif) includes the subsidy amount and the volume of R&D that was induced by the DPF grant. For not publicly funded firms the counterfactual R&D equals a firm's observed total R&D expenditures; the subsidy-related R&D is naturally zero. The regressions are based on a reduced sample since the output variables on the innovation success relate to the following one and two years and need to be taken from the two subsequent survey years. The results for the differentiation between these two types of R&D are shown in the left part of Table 6. Overall both types of R&D expenditures have a positive effect on R&D output, measured as sales with market novelties and the corresponding share in total sales. The two R&D variables tend to be equally productive since their coefficients are not statistically different. This is in line with the results found by Czarnitzki and Hussinger (2004), Czarnitzki and Licht (2006) and Hussinger (2008) for Germany. In contrast, for Flanders the impact on innovative output is even higher for publicly induced R&D than for the counterfactual R&D (Aerts, 2008).

In addition, R&D expenditures are separated for first-time and frequent recipients in order to get a more detailed view of the effectiveness for the two groups of firms. For this purpose the two R&D variables are interacted with dummy variables indicating the corresponding group. The advantage of this setup is that the coefficients of the subgroups are directly comparable (see the right part of the table). All three groups – no grants, first-time and frequent participants – seem to be able to realize the same scope of sales through their "counterfactual" R&D. In terms of the effect of R&D expenditure induced by the DPF grant, the impact on sales with market novelties is equally large for both types of participants. No statistically significant difference can be detected between any of the R&D variables in terms of the effectiveness to generate and sell new products.

Table 6: Subsidy effects on firm’s R&D output – overall and depending on DPF history

	Sales with market novelties (in € million, in ln)		Share of sales with market novelties (in %)		Sales with market novelties (in € million, in ln)		Share of sales with market novelties (in %)	
	t+1	t+2	t+1	t+2	t+1	t+2	t+1	t+2
Variable								
R&D_C	0.122	0.208	3.258***	4.711***				
	(0.270)	(0.188)	(0.988)	(0.922)				
R&D_C_no					0.970***	0.643***	3.786***	2.874***
					(0.134)	(0.083)	(0.503)	(0.472)
R&D_C_first					0.711	1.122***	3.283*	6.243***
					(0.524)	(0.349)	(1.757)	(2.335)
R&D_C_frequent					1.087**	0.504	6.684***	5.234***
					(0.519)	(0.397)	(1.946)	(1.657)
R&D_Dif	0.392	0.590***	4.281***	3.723***				
	(0.274)	(0.218)	(1.153)	(0.996)				
R&D_Dif_first					1.344**	1.604***	3.406	6.682***
					(0.695)	(0.460)	(2.147)	(1.611)
R&D_Dif_frequent					0.654	0.938**	5.687***	4.777***
					(0.549)	(0.393)	(1.854)	(1.302)
ln(Sales)	0.562**	0.838***	-0.760	1.257	0.095*	0.501**	0.754	2.099**
	(0.227)	(0.169)	(0.831)	(0.820)	(0.228)	(0.197)	(0.764)	(0.850)
ln(Sales)^2	-0.022	-0.062*	-0.173	-0.452***	-0.051	-0.078**	-0.252*	-0.470***
	(0.044)	(0.035)	(0.140)	(0.145)	(0.048)	(0.036)	(0.135)	(0.141)
ln(Patent_stock)	0.345***	0.224***	1.063***	0.793***	0.224**	0.133**	0.517*	0.471*
	(0.088)	(0.062)	(0.282)	(0.293)	(0.095)	(0.058)	(0.276)	(0.263)
Cooperation (d)	1.739***	1.070***	3.390***	3.604***	1.308***	0.710***	2.829**	3.380 ***
	(0.313)	(0.238)	(0.998)	(1.152)	(0.378)	(0.257)	(1.149)	(1.214)
East (d)	-1.299***	-0.755***	-3.722***	-3.345**	-1.648***	-0.986***	-4.981***	-4.339***
	(0.380)	(0.293)	(1.344)	(1.414)	(0.406)	(0.285)	(1.291)	(1.426)
Constant	-9.091***	-6.788***	-1.472	-4.783*	-6.209***	-4.807***	-5.884*	-7.833**
	(0.958)	(0.623)	(2.987)	(2.818)	(1.112)	(0.698)	(3.338)	(3.233)
Industry: Wald chi2(5)	13.26**	31.06***	13.16**	26.18***	4.06	7.84	6.24	10.56*
Year: Wald chi2(11)	43.33***	52.46***	34.20***	46.91***	48.97***	50.37***	40.69***	50.14***
Test on equality of coefficients: chi2(1)								
R&D_C=R&D_Dif	1.99	6.13**	0.66	1.28				
R&D_C_first=R&D_C_no					0.24	1.90	0.09	2.13
R&D_C_freq=R&D_C_no					0.05	0.13	2.15	2.08
R&D_C_first=R&D_C_freq					0.25	1.51	1.62	0.13
R&D_C_first=R&D_Dif_first					1.29	1.78	0.00	0.05
R&D_C_freq=R&D_Dif_freq					0.78	2.65	0.18	0.07
R&D_Dif_first=R&D_Dif_freq					0.61	1.27	0.66	0.88
Pseudo/adjusted R2	0.02	0.03	0.01	0.01	0.02	0.04	0.01	0.01
Wald chi2	250.46***	381.08***	147.92***	151.94.***	333.27***	420.07***	163.08***	152.39***
No. of obs.	3,942	3,540	3,942	3,540	3,718	3,335	3,718	3,335

Note: Coefficients and standard errors (in parentheses) are shown. Counterfactuals are firms with no DPF. For treated firms: R&D_C equals the counterfactual ln(total R&D), R&D_Dif is the treatment effect on ln(total R&D expenditures). For counterfactual firms: R&D_C is the observed ln(R&D), R&D_Dif equals zero. For regressions with share of sales with market novelties as dependent variable the corresponding R&D intensities are used. *** (**, *) indicates significance level of 1% (5%, 10%). Standard errors are clustered by firm and bootstrapped based on 200 replications.

The same analysis is conducted for the three groups of firms receiving different amounts of DPF grants (Table 7). Compared to not subsidized firms, firms who are recipients of large grants tend to translate the "counterfactual" R&D expenditures more effectively into innovation output. For the three types of DPF recipients the positive impact of their "counterfactual" R&D on the output is statistically the same. In addition, no differences in the effective use of the public grant and the induced R&D are detected between the three groups.

Table 7: Subsidy effects on firm's R&D output – depending on DPF grant size

	Sales with market novelties (in € million, in ln)		**Share of sales with market novelties (in %)**	
	t+1	**t+2**	**t+1**	**t+2**
Variable				
R&D_C_no	1.041***	0.646***	4.019 ***	3.290 ***
	(0.137)	(0.084)	(0.509)	(0.495)
R&D_C_small	1.208***	0.649***	4.746 ***	5.454 ***
	(0.391)	(0.252)	(1.367)	(1.250)
R&D_C_medium	1.058***	0.572*	5.925 ***	7.466 ***
	(0.388)	(0.305)	(1.294)	(1.473)
R&D_C_large	0.872*	1.030***	6.959 ***	6.185 ***
	(0.510)	(0.268)	(1.319)	(1.041)
R&D_Dif_small	0.928*	1.058***	5.052 ***	5.917 ***
	(0.557)	(0.360)	(1.761)	(1.134)
R&D_Dif_medium	1.350***	0.919***	6.249 ***	6.734 ***
	(0.457)	(0.333)	(1.454)	(1.651)
R&D_Dif_large	0.437	1.077***	4.871 **	4.678 ***
	(0.577)	(0.344)	(2.027)	(1.651)
ln(Sales)	-0.037	0.503***	0.772	2.596 ***
	(0.228)	(0.184)	(0.822)	(0.876)
ln(Sales)^2	-0.039	-0.081**	-0.256 *	-0.520 ***
	(0.042)	(0.035)	(0.143)	(0.140)
ln(Patent_stock)	0.199**	0.135**	0.558 **	0.358
	(0.086)	(0.061)	(0.278)	(0.257)
Cooperation (d)	1.274***	0.750***	1.975 *	2.456 **
	(0.362)	(0.255)	(1.132)	(1.147)
East (d)	-1.712***	-1.021***	-5.226 ***	-4.643 ***
	(0.403)	(0.318)	(1.314)	(1.504)
Constant	-5.547***	-4.672***	-5.414 **	-8.556 ***
	(0.917)	(0.665)	(2.634)	(2.924)
Industry: Wald chi2(5)	4.62	15.33***	7.01	14.90 **
Year: Wald chi2(11)	45.69***	36.40***	37.23 ***	42.44 ***
Test on equality of coefficients: chi2(1)				
R&D_C_small=R&D_C_no	0.19	0.00	0.30	3.27 *
R&D_C_medium=R&D_C_no	0.00	0.06	2.10	7.66 ***
R&D_C_large=R&D_C_no	0.12	2.11	4.63 **	8.31 ***
R&D_C_small=R&D_Dif_small	0.45	2.37	0.03	0.17
R&D_C_medium=R&D_Dif_med.	0.81	2.58	0.05	0.19
R&D_C_large=R&D_Dif_large	1.23	0.03	1.00	0.98
R&D_C_small=R&D_C_large	0.39	1.24	1.66	0.24
R&D_Dif_small=R&D_Dif_large	0.42	0.00	0.01	0.39
Pseudo R2	0.03	0.04	0.02	0.02
Wald chi2	364.39***	507.63***	225.27 ***	181.26 ***
No. of obs.	3,924	3,528	3,924	3,528

Note: Coefficients and standard errors (in parentheses) are shown. Counterfactuals are firms with no DPF. For treated firms: R&D_C equals the counterfactual ln(total R&D), R&D_Dif is the treatment effect on ln(total R&D expenditures). For counterfactual firms: R&D_C is the observed ln(R&D), R&D_Dif equals zero. For regressions with share of sales with market novelties as dependent variable the corresponding R&D intensities are used. *** (**, *) indicates significance level of 1% (5%, 10%). Standard errors are clustered by firm and bootstrapped based on 200 replications.

The control variables are in line with previous empirical findings. Firm's overall sales tend to have an inverse U-shaped impact on sales with market novelties although this effect is not always significant. The lagged patent stock as an indicator of past successful R&D increases sales with new products in the subsequent period. In addition, access to external knowledge with means of cooperation helps to increase innovative output. Firms located in the Eastern part of Germany are less successful in the generation and sales of market novelties.

6 Conclusions

In this paper the effects of public R&D grants on both the input and output of R&D activities are analyzed empirically. The knowledge about the grant size enables me to differentiate between partial crowding-out, additionality and no effect on R&D input. Based on these results the contribution of subsidies on R&D output is investigated. In the analysis I allow for heterogeneous effect in terms of two dimensions: firm's DPF history and DPF grant size. This paper contributes to understanding the effectiveness of DPF grants in stimulating private R&D and producing innovations.

Using a sample of about 4,000 German firms a non-parametric matching approach with multiple treatments is applied to firstly estimate the effects of public R&D subsidies on a firm's R&D input for different types of firms with respect to funding experience and grant size. For both first-time and frequent participants in the DPF scheme, full and partial substitution of privately-financed R&D expenditures by the subsidy can be ruled out on average. For frequent DPF recipients a stimulation of private R&D spending is found which can be attributed to the receipt of the grant. For first-time DPF participants no such effect can be observed. The findings suggest that firms experienced in receiving public R&D support and receiving grants over a longer period of time are able and also willing to increase their R&D efforts. This may be attributed to planning security effects that allow these firms to increase the level of risk, and thus also their private R&D investments. In terms of a firm's R&D output, the grant effect (i.e. the grant plus the private R&D expenditure induced by the grant) attributes to innovation success to the same extent as the "counterfactual" R&D (i.e. R&D expenditure less the grant and the induced private R&D) does. In addition, subsidy-related R&D is used equally efficiently by both first-time and frequent participants in terms of the generation of new to the market products. Overall no evidence is found that supporting the same firms leads to a lower effectiveness of the instrument. Although firms that received funding in the past are more likely to be selected for public funding again, this selection does not seem to have a negative impact on input and output effects.

Furthermore, this paper provides evidence on the role of grant size on firm's R&D. Small grants do not exhibit a significant effect on company-financed R&D expenditures. The results suggest that grants should have a minimum size to cause an impact on a firm's privately financed R&D. In contrast, medium- and large-scale grants increase firm's R&D spending. These findings suggest that firms indeed face financial constraints in particular for costly R&D projects firms. Since R&D expenditures often lack collaterals due to their intangible nature, usually these activities need to be financed with internal resources. The subsidy is therefore needed to realize the project. Another explanation is that the risk of a successful completion or market uncertainty of larger projects is too high for firms. Subsidies mitigate these issues since they directly reduce the costs. Czarnitzki and Toole (2007) provide empirical evidence for this relationship between subsidies and market uncertainty. Remarkably in terms of the generated innovation output by publicly induced R&D, the effectiveness of small grants is the same as for larger grants.

Overall positive effects of DPF grants on R&D input and also on output are found. The policy goal of increasing the investment in R&D is certainly achieved. However, not every grant has the same effect. The analysis provides evidence that (at least) the effect varies by a firm's history of receiving subsidies and by grant size. Besides the necessity of a minimum grant size, the effect of private R&D is higher for frequent participants. In addition, publicly induced money is translated into new products as effectively as privately financed R&D.

The results suggest that the government is successful in selecting projects which the firms would not have conducted without the grant. However, in recent years a trend towards the allocation of smaller grants can be observed, even in nominal terms. While in the mid-nineties the median grant equaled 61,000 euros in the population of DPF grants, ten years later the median grant consists of 42,000 euros. The results of the study suggest that the grants should not become too small in order to achieve stimulating effects.

Limitations and future research

Various caveats should be taken into account regarding the results. The change in R&D spending before and after receiving a DPF grant could be compared between the matched groups. In practice the duration of the grant – on average three years – would also have to be taken into account. For instance, if a firm already receives grants for a project for two years the privately-financed R&D expenditures in the preceding year might already be affected by the grant. It would be necessary to look at the expenditures before the first year of funding. Long time-series data would be required to perform such an analysis.

In cases where no effect on firm-financed R&D is observed, a re-allocation of private R&D expenditures within a firm still might have occurred since the projects are usually subsidized only up to 50 percent. The firm-financed share of the subsidized projects might be re-directed towards the funded project and not invested in other R&D projects. Alternatively, the funded project has been on the research agenda of the firm anyway but is extended in size due to the subsidy. Shifts of money on the project level are not regarded in this study since the aim of the government is to increase firms' overall R&D activities.

Most of the given DPF grants are part of a collaborative project. Already in the 1980s, the government began to fund projects conducted by consortia rather than individual firms. 90 percent of the DPF firms in the sample have at least one joint project, often with universities or other public research institutions. The part of the project conducted by other partners than the observed firm is not incorporated in the analysis although it might have an impact on R&D spending and also on the success of such a project as it is known from the literature on R&D co-operation in general. As an approximation for the second issue a dummy variable indicating whether a firm cooperates in its R&D activities – not necessarily in the subsidized project – is included in the estimation and it indeed increases R&D output. However, this relationship needs to be elaborated more precisely in further research.

This study investigated the effects depending on the absolute grant size. It would be interesting to also study the role of the relative grant size. It is conceivable that the grants should not be too high compared to previous R&D since the elasticity of R&D might be restricted.

DPF grants can have more effects than only the direct impact on the funded firm. Due to the nature of R&D, the funded firm cannot fully appropriate the results of the R&D project. Some knowledge generated within the publicly funded and induced R&D will spill over to other firms. A recent analysis for Germany conducted by Peters et al. (2009) shows that these indirect returns are even slightly higher than the direct, private returns and therefore not negligible. But negative effects on other firms also might occur, for example, due to competition distortion or a rise in wages for R&D employees. In addition, the instrument is accompanied with costs. Institutions responsible for the allocation of the grants need to be maintained. Costs are also involved on the company side for the application. A welfare analysis of the instrument which considers these issues is still lacking. I leave these questions to be explored in future research.

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Appendix A

Table 8: Matching protocol

Step 1	Specify and estimate a multinomial probit model to obtain the propensity scores $[\hat{P}_N^0(x), \hat{P}_N^1(x), ..., \hat{P}_N^M(x)]$.
Step 2	Restrict sample to common support: delete all observations whose probability is larger than the smallest maximum and smaller than the largest minimum of all subsamples 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 subsample defined by participation in *m* and delete it from that pool. (b) Find an observation in the subsample of participants in *l* that has the same value for Sub_EU, Sub_regional and year as the one chosen in Step (a) and is as close as possible to the one chosen in terms of $[\hat{P}_N^m(x), \hat{P}_N^l(x), \tilde{x}]$, with $\tilde{x}$ being a vector containing ln(employees) and ln(patent_stock_dev). 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. (c) Repeat a) and b) until no participant 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 effect using the results of Step 4. For statistical inference correct the standard errors using the approximation by Lechner (2001) since sampling with replacement is applied.

Note: Protocol is based on Gerfin and Lechner, 2002.

Table 9: Summary statistics of control variables

	Mean	Std. Dev.	Min	Max
Sub_EU	0.097	0.297	0	1
Sub_regional	0.207	0.405	0	1
ln(Employees)	4.537	1.567	0	8.517
ln(Age)	2.722	1.211	-0.693	5.318
R&D_con	0.716	0.451	0	1
Qualification	24.191	25.396	0	100
Ln(Patent_stock_dev)	-3.221	2.511	-4.987	5.244
Group_national	0.390	0.488	0	1
Group_foreign	0.115	0.319	0	1
East	0.327	0.469	0	1
Low tech ma.	0.098	0.298	0	1
Medium-low tech ma.	0.235	0.424	0	1
Medium-high tech ma.	0.333	0.471	0	1
High tech ma.	0.165	0.371	0	1
Low tech services	0.081	0.272	0	1
High tech services	0.089	0.284	0	1

Note: 8,528 obs. Year variables are not shown.

Table 10: Estimation results for the propensity scores

	DPF Probit	DPF history Multinomial probit		DPF size Multinomial probit		
		First	**Frequent**	**Small**	**Medium**	**Large**
	dy/dx (Std.Err.)	**dy/dx (Std.Err.)**	**dy/dx (Std.Err.)**	**dy/dx (Std.Err.)**	**dy/dx (Std.Err.)**	**dy/dx (Std.Err.)**
Sub_EU°	0.122***	0.022**	0.050***	0.028***	0.032***	0.046***
	(0.020)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Sub_regional°	0.062***	0.008	0.019***	0.023***	0.021***	0.013***
	(0.013)	(0.006)	(0.006)	(0.008)	(0.007)	(0.005)
ln(Employees)	0.026***	0.009***	0.006***	0.007***	0.005**	0.010***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
ln(Age)	0.003	-0.002	0.002	-0.001	0.003	0.000
	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
R&D_con°	0.069***	0.023***	0.014***	0.022***	0.029***	0.016***
	(0.009)	(0.004)	(0.003)	(0.005)	(0.005)	(0.003)
Qualification	0.002***	0.001***	0.000***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patent_stock_dev	0.013***	0.003***	0.004***	0.005***	0.005***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Group_national°	-0.014	-0.005	-0.001	-0.003	-0.006	-0.004
	(0.009)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)
Group_foreign°	-0.014	-0.013**	0.002	-0.008	-0.011*	0.004
	(0.014)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)
East°	0.006	0.006	0.004	-0.001	0.002	0.004
	(0.012)	(0.005)	(0.004)	(0.006)	(0.006)	(0.004)
Medium-low tech ma.°	-0.007	-0.013*	0.020	0.004	-0.017**	0.009
	(0.019)	(0.007)	(0.013)	(0.011)	(0.008)	(0.010)
Medium-high tech ma.°	0.016	-0.005	0.023**	0.011	-0.003	0.010
	(0.019)	(0.008)	(0.011)	(0.011)	(0.010)	(0.009)
High tech ma.°	0.065***	-0.000	0.063**	0.018	0.008	0.040**
	(0.027)	(0.009)	(0.025)	(0.014)	(0.012)	(0.019)
Low tech services°	-0.017	-0.015*	0.010	-0.003	-0.009	-0.001
	(0.022)	(0.008)	(0.013)	(0.013)	(0.011)	(0.009)
High tech services°	-0.006	-0.011	0.027	-0.020**	-0.007	0.021
	(0.024)	(0.008)	(0.020)	(0.008)	(0.011)	(0.016)
Wald chi2 all	573.83***	553.82***			696.82***	
Log likelihood	-2,671.69	-2,272.33			-3,804.64	
Mc Fadden's R2	0.196					
No. ob obs.	8,528	8,108			8,528	

Note: ° dy/dx is for discrete change of dummy variable from 0 to 1. *** (**, *) indicate significance level of 1% (5%, 10%). Standard errors are clustered by firm. Sector and year dummy variables are included in the regressions but not shown. Base categories in all estimations are firms with no DPF.

Appendix B

Different possibilities exist for the estimation of the propensity scores which enter the matching algorithm. Either multinomial choice models can be applied to obtain the probabilities of each treatment or conditional probabilities based on the subsample of participants in *m* and *l* are used. In order to identify the average treatment effect, it is sufficient to use information from the subsample of participants in *m* and *l* (Lechner, 2002). Lechner compares the two types of approaches and concludes that no approach is superior to the other per se. However, using propensity scores on the basis of the multinomial probit model inherent the risk that if one choice equation is misspecified, all conditional probabilities could be misspecified. Thus, as a robustness check the effects are calculated on estimations of the conditional probabilities between the pairs of choices directly with means of probit models. This estimation strategy is similar to the one used in the context of binary treatments. Since this approach produces a lot of probit models – three models for the analysis of the DPF history and six of the grant size – the probit results are not presented. Overall the results are very similar to those of the corresponding multinomial models. The resulting effects depending on DPF history and DPF size are shown in Table 11. Due to the less restrictive common support which is based only on the two treatments under analysis more observations are used.

Table 11: Average treatment effects on the treated – propensity scores based on probit models

		Outcome variable		
Treated (*m*)	**Control (*l*)**	**ln(private R&D)**	**ln(private R&Dint)**	**No. of matched pairs**
DPF history				
First DPF	No DPF	0.234	0.144	330
Frequent DPF	No DPF	0.371**	0.284**	354
Frequent DPF	First DPF	0.298	0.223	273
DPF size				
Small DPF	No DPF	0.142	0.119	370
Medium DPF	No DPF	0.325**	0.244**	368
Large DPF	No DPF	0.509***	0.313***	356
Medium DPF	Small DPF	0.159	0.043	326
Large DPF	Small DPF	0.714***	0.457***	303
Large DPF	Medium DPF	0.358**	0.065	327

Note: Average treatment effects on the treated ($\alpha^{m,l}$) are shown. *** (**, *) indicates significance level of 1% (5%, 10%) of the two-sided t-tests on mean equality between the treatment group *m* and the selected control group *l*. The standard errors of the t-statistics are based on the approximation by Lechner (2001) that accounts for sampling with replacement in the selected control group. All control variables as well as the propensity score are not significantly different between the two groups after matching. Sub_EU, Sub_regional and year variables are exact matches.

Appendix C

As a robustness check the analysis is repeated for a subsample of firms who do not receive subsidies from other sources, such as the EU or regional level. Hence, only firms who only receive DPF or no financial support are included in this subsample. Thus, these results are not biased due to other funding. But due to the exclusion of firms with support from other sources the number of observations decreased substantially. The subsample consists of 6,405 observations, instead of 8,528 observations (-25%). In particular the number of DPF participants decreased since these firms also receive funding from other sources (-49%). Since the probability of getting other funds is also higher for frequent recipients and firms with larger grants, the number of frequent and large recipients even decreases by 61 percent and 57 percent respectively. Thus, one has to bear in mind that in particular these groups might not represent the population of DPF recipients very well.

Table 12: Average treatment effects on the treated for the subsample of firms – no receipt of subsidies from EU or regional level

		Outcome variable		
Treated (*m*)	**Control (*l*)**	**ln(private R&D)**	**ln(private R&Dint)**	**No. of matched pairs**
Whole sample				
With DPF	No DPF	0.454***	0.371***	573
DPF history				
First DPF	No DPF	0.249	0.241	194
Frequent DPF	No DPF	0.401*	0.431**	141
Frequent DPF	First DPF	0.346	0.399**	126
DPF size				
Small DPF	No DPF	0.217	0.184	202
Medium DPF	No DPF	0.355*	0.319**	185
Large DPF	No DPF	0.712***	0.457***	159
Medium DPF	Small DPF	0.293	0.170	180
Large DPF	Small DPF	0.809***	0.215	155
Large DPF	Medium DPF	0.408*	0.188	147

Note: Firms who receive subsidies from the EU or regional level are dropped. Average treatment effects on the treated ($\alpha^{m,l}$) are shown. *** (**, *) indicates significance level of 1% (5%, 10%) of the two-sided t-tests on mean equality between the treatment group *m* and the selected control group *l*. The standard errors of the t-statistics are based on the approximation by Lechner (2001) that accounts for sampling with replacement in the selected control group. All control variables as well as the propensity score are not significantly different between the two groups after matching. Sub_EU, Sub_regional and year variables are exact matches.