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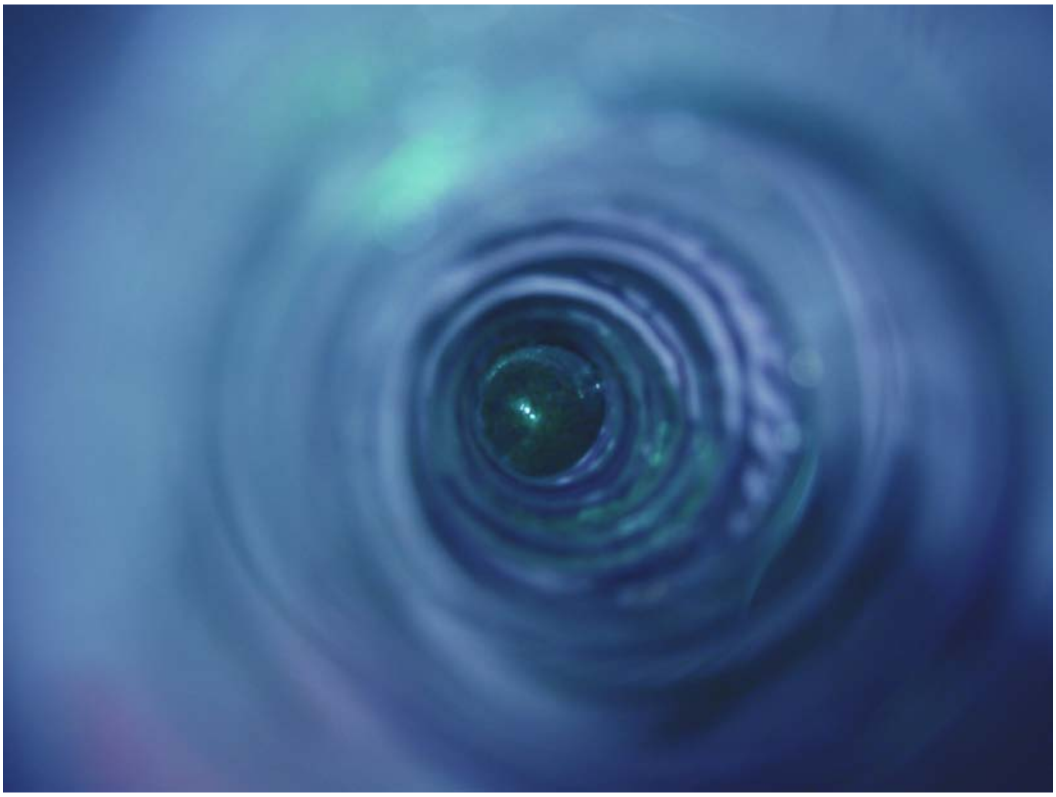

Effects of Public R&D Funding

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Abstract
The aim of this research is to investigate the incentive effects of the funding instruments of the Finnish Funding Agency for Technology and Innovation (Tekes). The data basis for this analysis is the forth wave of the Community Innovation Survey covering the years 2002 to 2004. In addition the analysis uses the database on business subsidies maintained by the research lab of Statistics Finland. The database includes information on public direct business subsidies and loans at the firm level for years 2000–2005. It also includes the business subsidies and loans granted and paid by Tekes.

The results based on the microeconometric propensity score matching technique show that the public R&D funding has a significant positive effect on the innovation inputs, innovation outputs and on the collaboration breadth and depth of the funded companies. The stochastic frontier analysis reveals that the public R&D funding reduces the inefficiency of the innovation production process. The input into the innovation process is captured by the innovation expenditures. The innovation output is proxied by the number of patent applications.

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Preface

The authors thank Tekes for funding this project. All statistical analyses in this project have been carried out in the Research Lab of Statistics Finland. The research could not have been possible without the assistance of Tekes and the Research Lab. Especially the authors would like to thank Jari Hyvärinen and Jouko Retti from Tekes and Satu Nurmi from Statistics Finland for data preparation, as well as all those that commented on the research in the seminars of Tekes.

The views given in this report are those of authors and do not necessary reflect the views of Tekes, VTT or the Management Center Innsbruck.

Espoo and Innsbruck, June 2008

Bernd Ebersberger

Olavi Lehtoranta

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1. Introduction

An analysis of the effects of public intervention is warranted for reasons of accountability and transparency of public spending. Public support for private innovation activities should only be exercised if they increase innovation output (*output additionality*). Increasing innovation output can be achieved in two ways, which are not mutually exclusive. Rather would we argue for their complementarity. First, public support can target market failure which commonly leads to underinvestment in innovation activities (Arrow, 1962; Nelson, 1959). Clearly, public support tries to increase private innovation input (*input additionality*) and to achieve output additionality. Second, public support strives to make a difference by inducing behavioral change among the supported companies (*behavioral additionality*).

1.1 Questions

The questions posed for this research are to analyze all three dimensions of additionality based on Finnish innovation survey data. The final target of this paper is to deliver one piece of information to the overall evaluation and assessment of public support for private innovation activities in Finland.

This analysis can also be seen as a continuation and extension of the analysis in Ebersberger (2004), Ebersberger (2005), Ebersberger & Lehtoranta (2005) and Czarnitzki, Ebersberger & Fier (2007).

1.2 Brief literature review

The empirical evidence in the literature about the effect of public funding is not unanimous (David, Hall & Toole, 2000; Hall, 2005). In some cases the literature finds that public subsidies exhibit positive effects on private R&D expenditure (Busom, 2000; Duguet, 2004; Licht & Stadler, 2003; Fier, Heger & Hussinger, 2004). Toivanen & Niininen, (2000) concentrate on the relationship between credit constraints and the effectiveness of R&D subsidies. Their empirical study of Finnish firms suggests that R&D subsidies are most effective when directed at firms affected by modest credit constraints. In the most recent studies Schmidt & Aerts (2006) reject the hypothesis of crowding out both for German and for Flemish data based on an analysis employing a conditional difference-in-difference estimator for repeated cross sections. Using microeconometric matching Czarnitzki & Licht (2006) also reject crowding out of private innovation expenditure. Based on parametric and semi-parametric selection models Hussinger (2008) finds positive effects of public funding.

Other studies such as Wallsten (2000) conclude that public subsidies crowd out private R&D investment. Lach (2002) shows that public funding crowds out private innovation investment in large enterprises.

Concerning the output additionality Czarnitzki & Fier (2003) and Czarnitzki & Hussinger (2004) analyze the patenting behavior of German firms. They find positive effects of public funding. In addition, publicly funded R&D consortia have a higher propensity to patent than privately financed consortia.

For Finnish firm-level data, Ebersberger (2004), Ebersberger & Lehtoranta (2005) and Ebersberger (2005) show that funding for cooperative R&D increases the innovation output in terms of patenting. For a small subset of firms and projects they also find a positive effect of public funding on the labor demand of funded firms in the medium term. In a comparison study for German and Finnish data Czarnitzki, Ebersberger & Fier (2007) find positive effect on innovation input on innovation output and innovation performance for the Finnish data. The results for the German data are not so pronounced when innovation output and innovation performance is considered.

2. Data

The data basis for this analysis is the Community Innovation Survey (CIS). The CIS, was commenced in 1991 by Eurostat and the Innovation and SME Program. It aims at improving the empirical basis of innovation policy at the European and the Member State level. It surveys the innovation activities at the enterprise level in the Member States' economies. The CIS surveys collect firm-level data on innovations across member states by means of largely harmonized questionnaires. Thus the data are comparable on the European scale and are based on a representative sample of companies within these economies. For academic research as well as for informing policy decisions the Community Innovation Survey provides a rich and unique source of information on literally all dimensions of innovation activities on the firm level. The definitions and concepts employed in the survey correspond to the OECD’s Oslo Manual.

In this analysis we use the forth wave of the Community Innovation Survey covering the years 2002 to 2004. CIS data has been used for assessing the effects of public innovation support in a number of cases (Aerts & Czarnitzki, 2004; Almus & Czarnitzki, 2003; Ebersberger, 2005; Czarnitzki, Ebersberger & Fier, 2007; Hussinger 2008).

In addition the analysis used the database on business subsidies maintained by the research lab of Statistics Finland. The database includes information on public direct business subsidies and loans at the firm level for years 2000–2005. It also includes the business subsidies and loans granted and paid by the Finnish Funding Agency for Technology and Innovation (Tekes). However, there is no breakdown on type of innovation. The database does not include tax incentives. This data can be linked with other firm level information using common unit identifiers (protected firm codes).

2.1 Characterizing the data

The analysis confines itself to the investigation of innovation active companies with 2500 or less employees. Anticipating the used methodologies – such as nearest neighbor matching, to be elaborated upon in section 3 – deleting the largest companies from the data set will ensure better applicability of the matching methodology.

Furthermore it is reasonable to assume that companies not carrying out innovation activities are per se not interested in support activities for their (non existing) innovation activities. Hence, these companies are not in the key focus of this analysis. Restricting the analysis to innovation active companies is also decision commanded by the peculiarities of the data source used here. The CIS survey questionnaire contains some filter-questions based on the innovation activities of firms. Some questions, e.g. the questions about innovation collaboration are not presented to companies without innovation activities. Our definition of innovation activities which qualify a company to enter the analysis data set strongly reflects the notions of innovation activities as carried both by the CIS core questionnaire and the OECD's Oslo Manual. For this analysis we regard companies as innovation active if they introduce a product innovation or a process innovation, carry out a not finalized innovation project or abandoned an innovation project during the reference years of the survey. This definition is inline with the traditional use of CIS data.

After the initial cleaning the overall data set contains 1,032 observations. For 303 observations received public support for their innovation activities. Descriptive statistics for the data set are displayed in Table 1; correlations between key variables in the analysis can be found in Table A1 in the Appendix.

Table 1. Descriptive statistics of key variables.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Size (employees)	1032	168.92	279.07	2	2390
Size (log employees)	1032	4.32	1.27	0.69	7.78
R&D department	1032	0.73	0.44	0	1
Patent stock	1032	0.26	0.44	0	1
Export intensity	1032	0.43	0.40	0	1
Appropriability	1032	0.09	0.06	0	0.23
Innovation expenditure	853	1870.15	13598.42	0	376612
Innovation intensity	1032	0.22	0.38	0	1
Patent application	1032	0.18	0.38	0	1
Nu. of patent appl.	1032	1.12	5.91	0	123
Pat. appl. / R&D empl.	1032	0.02	0.06	0	0.75
Innovation (new to market)	1024	0.50	0.50	0	1
Sales share of innovation	1028	0.08	0.16	0	1
Sales share of (n.t.m.) innov.	1028	0.06	0.13	0	1
Collaboration breadth	498	0.81	0.25	0	1
Collaboration depth	497	0.13	0.15	0	0.67
Public support	645	0.47	0.50	0	1
Collaboration for innovation	1004	0.50	0.50	0	1
High technology manuf.	1032	0.03	0.18	0	1
Medium high tech. manuf.	1032	0.21	0.41	0	1
Medium low tech. manuf.	1032	0.17	0.38	0	1
Low tech. manuf.	1032	0.17	0.38	0	1
Knowledge int. serviced	1032	0.20	0.40	0	1
Other services	1032	0.21	0.41	0	1

2.2 Indicators for innovation input, output and performance

In this analysis we use the usual indicators for innovation input: innovation expenditure and innovation intensity. The latter is the share of turnover invested in innovation activities.

The innovation output is captured by the number of patent applications. Although being aware of the shortcomings of this measure, patent applications as a dummy or the number of patent applications have been suggested by Haagedorn & Cloodt (2003) and used in the evaluation context by Czarnitzki & Fier (2003), Czarnitzki & Hussinger (2004), Czarnitzki & Licht (2006) and Czarnitzki, Ebersberger & Fier (2007).

Public support is initially captured by a dummy variable. In later stages of the analysis dummy variables indicating the receipt of subsidies and the receipt of loans are used to differentiate these instruments.

The behavioral dimension of the innovation process is captured by indicators for innovation collaboration. Following the notion of breadth and depth in Laursen & Salter (2006) two dimensions of innovation collaboration are distinguished. Collaboration breadth indicates the diversity of the collaboration network which is utilized for innovation activities. Collaboration depth captures the intensity of collaboration within the diverse set of collaboration partners. The higher the collaboration breadth the more diverse is the collaboration network and the higher the depth the more intensely the collaboration is which certain partners in the network.

3. Innovation input and innovation output

3.1 Methodology

The impact assessment methodologies revolve around the evaluation problem that occurs if – as is common in social science and economics – no experiments can be conducted. Briefly, the evaluation problem exists because, at any given point in time, a firm can be either treated or not treated.[1] A firm cannot be treated and not treated at the same time. Hence the difference in behavior or performance – which we denote as the effect of the treatment – cannot be observed directly. For the treated companies we can only observe their behavior and performance for the state of treatment. To assess the impact of treatment we would have to know what the company would have done and how it would have performed in the case of not being treated. This is the counterfactual situation for treated firms. Hence it is not observable. This missing data problem lies at the core of the evaluation problem.

The missing data problem will be solved by estimating the counterfactual behavior of the treated firms. One possibility to estimate the counterfactual would be to take the average behavior of the non-funded firms as an approximation of the counterfactual behavior of the funded firms. However, this does not lead to a valid estimate of the effects of public funding as – secondly – the average funded firm has different characteristics than the average not-funded firm. This difference is caused by the fact that receiving funding cannot be regarded as a purely random process. Rather, the differences in characteristics indicate a strong selection bias (Reinowski, 2006).

The analysis below tackles these problems by employing a microeconometric matching technique. For each treated – i.e. supported – firm the matching analysis finds an untreated company which is comparable to the treated one in a given set of firm characteristics. Then the difference in average behavior of the treated and the matched non-treated firms is an estimate for the mean treatment effect of public funding, as the behavior of the non-treated firms can be shown to be an estimate for the counterfactual behavior when the conditional independence assumption holds.[2]

Let Y^T be the behavior of the treated firms ($d = 1$) and let Y^C be the behavior of the firms in the control group of not supported firms. The matching estimator estimates the effect α_T of the treatment on the treated by comparing their behavior with the behavior of the counterfactual.

[1] In the discussion of the methodological approach to assess the impact of governmental intervention we will use the term treatment as a generalization for public support.

[2] A concise discussion on methodologies for non-experimental data in economics and social sciences can be found e.g. in Blundel & Costa-Dias (2000) or in Reinowski (2006).

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

The conditional independence assumption states that given the exogenous and observable characteristics *X,* the non-treated firms' behavior is the same as the treated firms' behavior, had the treated not been treated (Rosenbaum & Rubin, 1983; Rubin, 1977). Phrased differently, the selection only occurs on observables.

$$Y^C \perp d \mid X \tag{2}$$

The procedure to carry out a matching generally takes an observation *i* in the treated sub-sample and finds an observation *j* in the not treated subsample where $\left\| X_i - X_j \right\|$ is minimized. However, it is evident that the larger the set of exogenous characteristics in *X,* the harder it is to find an appropriate observation *j* to match the given characteristics of observation *i*. This phenomenon is vividly phrased as the *curse of dimensionality*. An elegant and therefore extremely workable solution to the problem is offered by Rosenbaum and Rubin (Rosenbaum & Rubin, 1984; Rosenbaum & Rubin, 1983). They show that under the given assumptions controlling for the propensity to receive support conditional on *X* instead of controlling for *X* directly yields a valid estimate of the counterfactual. Inline with the tradition – from Czarnitzki & Fier (2002) and Czarnitzki & Fier (2003) to Schmidt & Aerts (2006) – we document how we proceed in the matching by summarizing the procedure in the matching protocol in Table 2.

Table 2. Matching protocol.

Step 1	Specify and estimate a probit model to obtain the propensity scores.	
Step 2	Restrict the sample to common support: delete all observations among the funded firms with probabilities larger than the smallest maximum and smaller than the largest minimum of the non-funded firms.	
Step 3	Estimate the counterfactual expectations of the innovation input, innovation output und innovation performance / behavior variables for the funded companies	
	a)	Choose one observation in the sub-sample of the funded companies and delete it from the pool.
	b)	Compute the distance (in terms of likelihood of receiving funding) of any not supported company to the funded company. Select the observation from companies which has minimal distance to the funded company. Add this observation to the group of matched comparisons. Put this observation back to the set of not supported companies to allow for selection with replacement.
	c)	Repeat a) and b) until no observation is left in the sub-sample of funded companies.
	d)	Using the matched comparison group formed in c), compute the respective conditional expectation by the sample mean.
Step 4	Compute the estimate of the treatment effects using the results of Step 3.	

3.2 Results

The results of the analysis are discussed in two sections. The first section discusses the results of the matching procedure, where we put special focus on the discussion of the selection bias. The second section reports the estimated effects of public support based on the matched samples.

3.2.1 Matching

Table 3 displays the probit regressions used to illustrate how the matching procedure soothed the selection bias problem in the initial sample. The first two result columns of Table 3 show how different company characteristics determine the public support. Companies receiving public support tend to be larger, carry out innovation activities in an institutionalized R&D department, exhibit more innovation and technological experience (as proxied by the patent stock) and finally they have a higher export orientation. The latter however is not significant. Overall the company characteristics jointly determine the public support. These observations indicate a strong selection bias being present in the data set with respect to government support for innovation.

Table 3. Determinants of public funding.

	before matching		after matching	
Public support	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Size (log employees)	0.141***	0.047	-0.035	0.045
R&D department	1.011***	0.180	0.267	0.244
Patent stock	0.582***	0.121	0.166	0.110
Export intensity	0.209	0.152	-0.188	0.151
Appropriability	-0.523	1.275	0.020	1.320
Constant	-2.425	0.591	-0.132	0.705
Nu. of obs.	645		606	
LR chi2(11)	168.4***		5.31	
R2	0.189		0.006	
LL	361.7		-417.4	

Note: ***(**, *) indicates significance at the 1%, (5%, 10%) level. 6 sector dummies included in the regressions are not reported here.

The second section in Table 3 displays the explanatory power of the same regression after the matching. The 303 publicly supported companies were matched to similar not supported companies where similarity is measured by the likelihood to receive funding. The likelihood was estimated based on the probit regression reported in the left part of

Table 3. The probit regression after the matching does not reveal any explanatory power as the estimated parameters are neither individually nor jointly significant. After the matching the selection bias (on the observed variables) has vanished which we found evidence for in the left part of the table.

3.2.2 Effects of public support

The effects of the support as experienced by the supported companies can be displayed as the difference between the innovation input (resp. the innovation output or behavior) of the supported companies and their counterfactual input, which we have estimated by the matched companies. In the graphical display below the mean input (resp. the innovation output or behavior) of the supported companies and their mean counterfactual input are illustrated by the light white bars. The effect of public support is displayed as a solid gray area. In the case of a statistically significant effect at least at the 10% level the bar is shaded with dark gray.

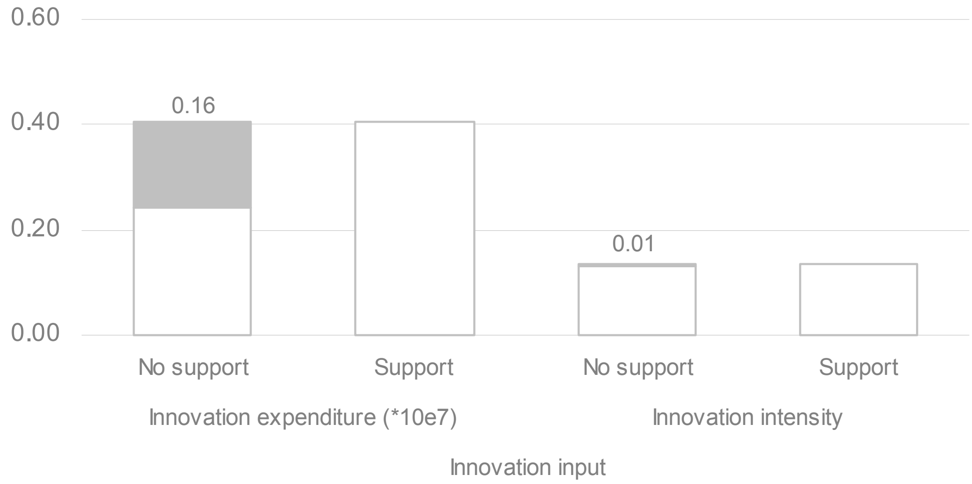

Figure 1. Innovation input effects of funding.

In Figure 1 we display the effect of public support for innovation on innovation input of the supported companies. In both innovation input dimensions – the innovation expenditure and the innovation expenditure as a fraction of sales i.e. the innovation intensity – we observe positive effects. In the case of the innovation expenditure they are rather sizeable; in both cases not significantly, though.

The effect on the innovation output dimensions is presented in Figure 2 and Figure 3. We observe a strong positive output effect of public support. Companies which receive public support have significantly higher propensity to apply for at least one patent. In addition they also show a higher average number of patents.

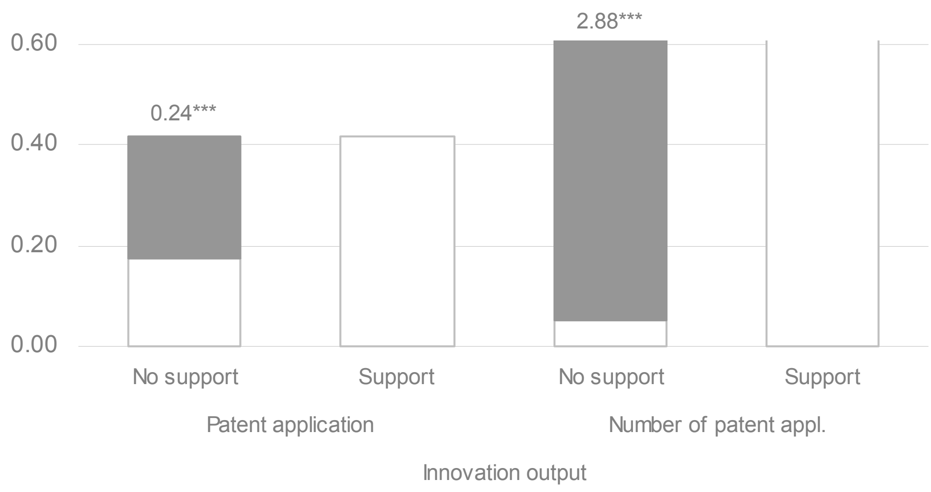

Figure 2. Innovation output effects of public support.

The innovation output of the supported companies and their counterfactuals displayed in Figure 3 also indicate a significantly positive effect of support on the share of sales generated by new products and services. This positive effect holds for both analyzed degrees of novelty: supported companies generate a share of sales from new products and services and a share of sales by market novelties which is significantly larger than the share would have been in the case of no support.

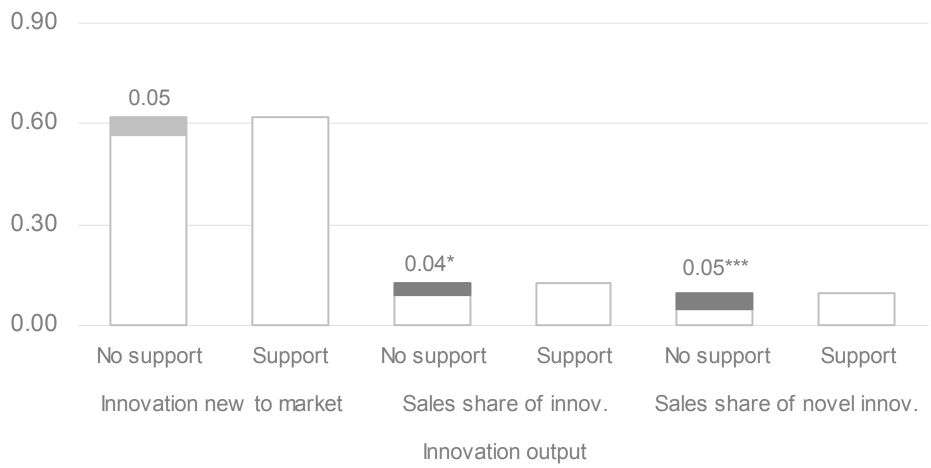

Figure 3. Innovation output effects of public support.

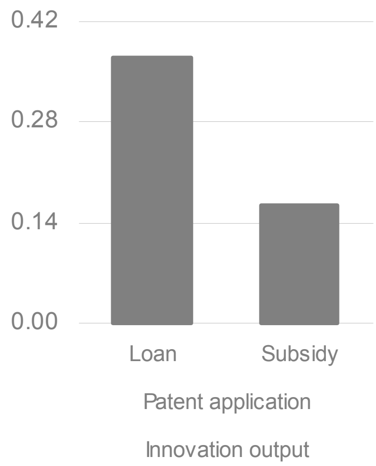

Figure 4. Innovation output effects of loans and subsidies.

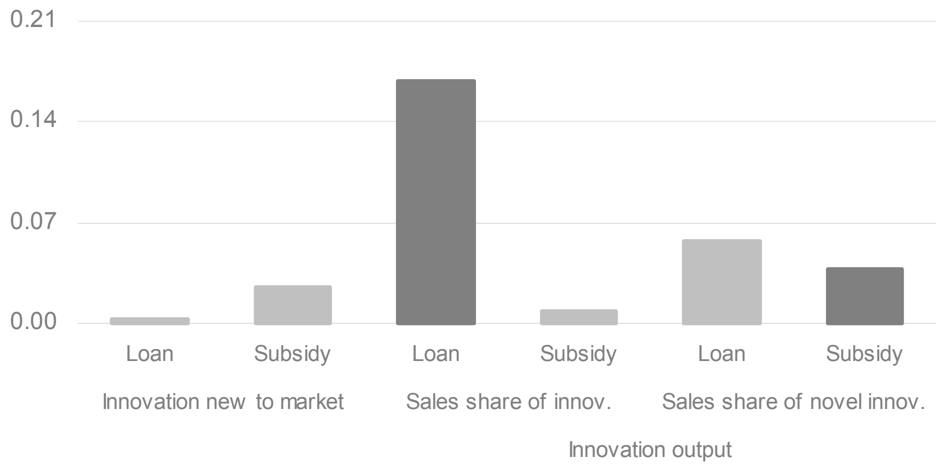

Figure 5. Innovation output effects of loans and subsidies.

Figure 4 and Figure 5 analyze the effect for different types of public support; the recipients of loans are distinguished from the recipients of subsidies. The diagrams display the effect of the respective instrument on the supported companies measured against the counterfactual situation. Significant effects at least at the 10% level are represented by dark shaded bars whereas non-significant effects are shades in light gray. Both types of support have a positive effect relative to the counterfactual situation.

For the introduction of product innovations which are new to the market only loans seem to yield a significantly positive effect in neither of the instruments. The sales share of new products and services is positively affected by the receipt of a loan whereas no significantly positive effect is found for the subsidies. The sales share of products and services which are new to the market is positively affected by loans and subsidies; only the latter is significant, though.

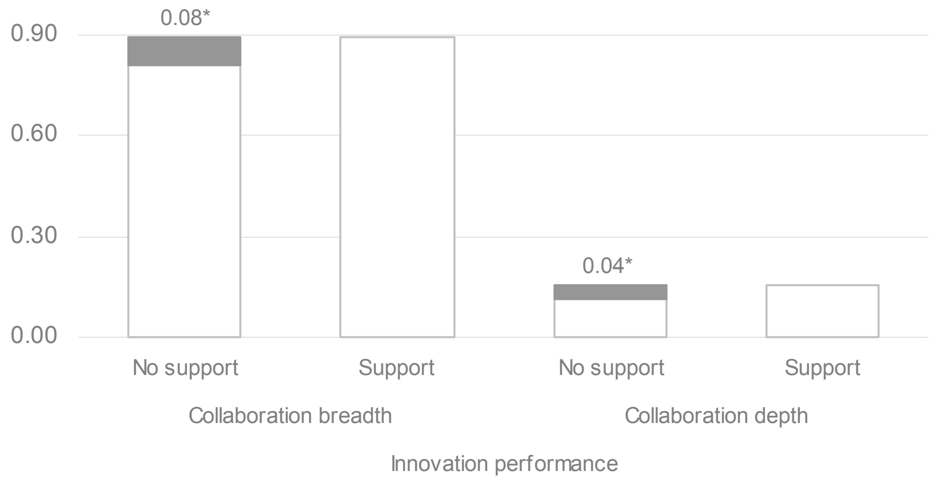

Figure 6. Innovation behavior effects of public support.

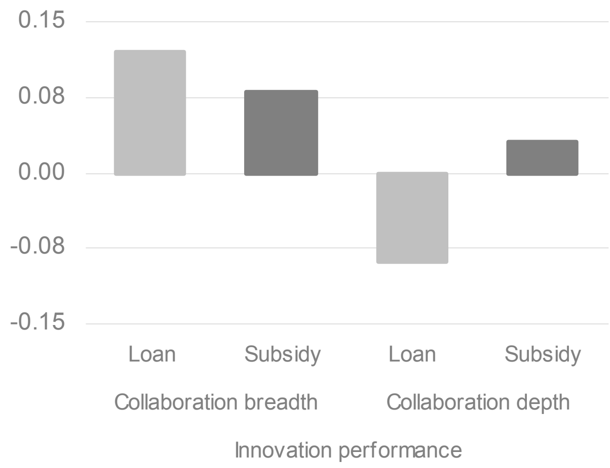

Figure 7. Innovation behavior effects of loans and subsidies.

Figure 6 and Figure 7 document the effects of public support on the innovation behavior where innovation behavior is measured as the pattern of collaboration for innovation. We observe that supported companies exhibit a significantly broader and deeper collaboration strategy in the context of innovation activities than they would have in the case of not being supported. When distinguishing the types of instruments only the subsidies cause collaboration to be broader and deeper. The effects of loans are not significant (Figure 7).

4. Effects on innovation productivity

4.1 Methodology

Applying the notion of innovation input and innovation output suggests implicitly the existence of an innovation production function (Griliches, 1998). Based on the innovation production function a notion of efficiency in the sense of Farrell can be elaborated upon (Farrell, 1957). A production unit is efficient if its output does not fall behind the output which is theoretically feasible given the production function and a given set of inputs. Assessing the degree of efficiency – or the degree of inefficiency – one would have to know the production function governing the transformation of innovation input into innovation output. The production function has to be estimated. Typically there exist two ways to do so in the context of efficiency measurement. First, the production function can be estimated by non-parametric techniques such as data envelopment analysis (Banker, Charnes & Cooper, 1984; Charnes, Cooper & Rhodes, 1978; Ray, 2004; Cooper, 2007). The non-parametric approach assumes that all deviations from the production function indicate inefficiency. Typically there is no stochastic component for measurement error and the like. Second, the production function can be estimated by parametric approaches. In contrast to the non-parametric approaches the parametric estimation also considers random deviation from the production function to be either the realization of inefficiency or random shocks. For the analysis of the innovation productivity we will follow a parametric approach and employ the stochastic frontier analysis (SFA). The stochastic frontier estimation is introduced by Aigner, Lovell & Schmidt (1977) and van den Broek & Meussen (1977). The basic idea in the stochastic frontier concept is that the estimation of the production function is carried out subject to two errors. In the linear production function below v_i captures the random shock whereas u_i captures the inefficiency.

$$y_i = f(x_i \beta) + v_i - u_i \tag{3}$$

where v_i is normally distributed. The inefficiency u_i depends on exogenous characteristics z_i.

$$u_i = z_i \delta_i + w_i \tag{4}$$

where w_i is truncated normally distributed (Battese & Coelli, 1995). This approach will be used to assess the inefficiency of the innovation production process. Incorporating indicators of public support in the equation determining the inefficiency we can estimate the effect of public support on the inefficiency when transforming innovation inputs into innovation outputs.

Due to the limitations posed by the cross-sectional nature of the data set we confine the analysis to a rather simple model of the underlying production function. The input into the innovation process is captured by internal innovation expenditure and by external innovation expenditure. The innovation output is proxied by the number of patent applications. Sectoral dummies are included to capture the heterogeneity across sectors.

4.2 Results

Table 4 displays the results of the stochastic frontier regression of the two-factor model of innovation production. Although being a rather simple setup the variables in the model jointly determine the innovation output, significantly. Both factors of innovation input – innovation expenditure spent in-house and innovation expenditure for purchased innovation services – yield an estimate of similar magnitude. Without going into deep detail we conclude here that marginal product of both types of innovation expenditure is equal and significantly larger than zero.

Table 4. Inefficiency of the innovation process (SFA).

Number of patent applications	**Coef.**	**Std. Err.**
Production function (equation 3)		
Innov. exp. internal	0.001***	0.000
Innov. exp. external	0.001***	0.000
Constant	1.978	18.824
Inefficiency (equation 4)		
Public support	-1.245*	0.711
Constant	1.382	18.645
Gamma	0.0001***	
Nu. of obs.	336	
Wald chi2(8)	183.91***	
LL	-1074.467	

Note: ***(**, *) indicates significance at the 1%, (5%, 10%) level. 6 Sector dummies included in the production function regressions are not reported here.

The hypothesis that all deviation from the production frontier is due to random shocks v_i is rejected by $\gamma = \sigma_u^2 / \sigma^2$ being significantly different from zero (Battese & Coelli 1995). The deviation from the production function is significantly determined by the public support. Companies which receive public support exhibit a significantly smaller inefficiency in transforming innovation inputs into innovation outputs.

The analysis in Table 5 differs from the previous analysis in the fact that the public support is now differentiated into loans and subsidies. Still, jointly the variables in the model determine the innovation output significantly. Both input factors into the innovation process reveal a comparable marginal product which is also significantly positive.

Table 5. Inefficiency of the innovation process (SFA).

Number of patent applications	**Coef.**	**Std. Err.**
Production function (equation 3)		
Innov. exp. internal	0.001***	0.000
Innov. exp. external	0.001***	0.000
Constant	3.245	6.120
Inefficiency (equation 4)		
Loan	-3.699	44.590
Subsidy	-1.673**	0.773
Constant	2.809	5.533
Gamma	0.0001***	
Nu. of obs	336	
Wald chi2(8)	184.25***	
LL	-1073.183	

Note: ***(**, *) indicates significance at the 1%, (5%, 10%) level. 6 Sector dummies included in the production function regressions are not reported here.

Testing the existence of inefficiency rejects the null about no inefficiency $-.\gamma$ is significantly different from zero. Both subsidies and loans reveal a positive effect on the reduction of inefficiency. The effect of loans is not significant, though.

5. Discussion

The analysis in this study can be seen as a continuation of the work in Ebersberger (2004), Ebersberger (2005), Ebersberger & Lehtoranta (2005), Czarnitzki, Ebersberger & Fier (2007). The analysis here extends into a more recent data and into the effect of public support for innovation on the innovation performance of companies. By innovation performance we mean the degree of efficiency by which companies transform innovation inputs into innovation outputs. The results obtained here differ somewhat from the results previously found.

In particular the effects of public support on private innovation expenditure is found to be positive, yet not statistically significant. The analysis in Ebersberger (2005) and Czarnitzki, Ebersberger & Fier (2007) had either no amount of funding available or was restricted to use estimated funding sums. Additionally, it seems that the skewed distribution of innovation expenditure has an influence on increasing the standard error of the mean estimate. Even though the effect is not statistically significant public support induces an economically important effect. The average private increase in innovation spending amounts to about 1,200,000 Euros induced by an average funding sum of 420,000 Euros. The average input effect is in the same magnitude as discussed in Ebersberger (2005) for Finnish data and Fier, Heger & Hussinger (2004) for German data.

The positive and significant innovation output effect as measured by the patent application dummy is comparable to the effects found in Czarnitzki & Fier (2003), Czarnitzki & Licht (2006), Ebersberger (2005), and Czarnitzki, Ebersberger & Fier (2007). The magnitude of the innovation output effect as measured in the number of patent applications is likely to be influenced by skewness of the patenting distribution (Scherer & Harhoff, 2000); i.e. a few supported companies patent more heavily than their estimated counterfactuals. The positive results here conform to the findings in Czarnitzki & Licht (2006) for East Germany and Czarnitzki, Ebersberger & Fier (2007) for Finland. The innovation output effects which we found for the sales share of innovation indicate that public support does not only make a difference in the earlier stages of the innovation process which is covered by the patenting variables. It does rather also make a difference in more advanced stages which are closer to the commercialization of the innovation such as product development and design.

In our analysis of the behavioral dimension we find significant impact of public support on the collaboration structure and intensity. However, only subsidies induce collaboration to be broader and deeper. In our analysis loans do not induce a significantly different collaboration behavior. As the analysis of the funding instruments (elsewhere) shows, loans are more likely given to product development projects. Given the nature of product development projects the not significant structural effect of loans seems sensible. From a firm perspective product development projects may be regarded as more sensitive in terms of direct competitive effects; hence intensive horizontal collaboration with competitors is less likely. Also product development projects are more on the applied spectrum of the R&D continuum. The deep integration of universities and research institutes for basic research seem less likely. When subsidies are handed out to more risky and more basic projects the intensive integration of other collaboration partners may be a way to reduce the risk and to manage the knowledge requirements for such a project.

Our analysis also shows that the efficiency of the innovation process is determined by public support. Companies with public support show a lower degree of inefficiency of their innovation process. They are capable of transforming given innovation input into higher rate of innovation output. The sources of this efficiency gap are cannot be fully analyzed. However, the fact that subsidies have a significantly positive effect on the transformation of inputs into output and loans have not, allows us to tentatively suggest two connections. First if loans are more likely to be given to project which are closer to the commercialization stage the room for organizational and innovation process improvements maybe tight. Second, as subsidies have been identified to spur broader and more intensive innovation collaboration these structural changes in the innovation process may indeed lead to the improved performance in the innovation process of the subsidized companies. These structural changes may also induce changes in the management of projects ect. which in turn increase the efficiency of the innovation process.

References

Aerts, K. & Czarnitzki, D. (2004). Using innovation survey data to evaluate R&D policy: The case of Belgium. *ZEW Discussion Papers* (04-55).

Aigner, D. J., Lovell, C. A. K. & Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics, 5,* 21–38.

Almus, M. & Czarnitzki, D. (2003). The Effects of Public R&D Subsidies on Firms Innovation Activities: The Case of Eastern Germany. *Journal of Business & Economic Statistics, 21,* 226–236.

Arrow, K. J. (1962). Economic Welfare and the allocation of resources for invention. In R. R. Nelson (Hrsg.). *The rate and direction of inventive activity.* Princeton: Princeton University Press.

Banker, R. D., Charnes, A. & Cooper, W. W. (1984). Some models for Estimation Technical and Scale Inefficiencies in data envelopment analysis. *Management Science, 30,* 1078–1092.

Battese, G. E. & Coelli, T. (1995) A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics, 20*, 325–332.

Blundel, R. & Costa-Dias, M. (2000). Evaluation methods for non-experimental data. *Fiscal Studies, 21,* 427–468.

Busom, I. (2000). Empirical evaluation of the effects of R&D subsidies. *Economics of Innovation and New Technology, 9* (2), 111–148.

Charnes, A., Cooper, W. W. & Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research, 2,* 429–444.

Cooper, W. W. (2007). *Data envelopment analysis* (2. ed.). New York NY: Springer (a comprehensive text with models, applications, references and DEA-solver software).

Czarnitzki, D., Ebersberger, B. & Fier, A. (2007). The relationship between R&D collaboration, subsidies and R&D performance: Empirical evidence from Finland and Germany. *Journal of Applied Econometrics 22,* 1347–1366.

Czarnitzki, D. & Fier, A. (2002). Do innovation subsidies crowd out private investment? Evidence from the German Service Sector. *Konjunkturpolitik, 48* (1), 1–25.

Czarnitzki, D. & Fier, A. (2003). Publicly funded R&D collaboration and patent outcome in Germany. *ZEW Discussion Papers* (03-24).

Czarnitzki, D. & Hussinger, K. (2004). The link between R&D subsidies, R&D spending and technological performance. *ZEW Discussion Papers* (04-56).

Czarnitzki, D. & Licht, G. (2006). Additionality of public RD grants in a transition economy: The case of Eastern Germany. *Economics of Transition, 14,* 101–131.

David, P. A., Hall, B. H. & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy, 29,* 497–529.

Duguet, E. (2004). Are R&D subsidies a substitute or complement to privately funded R&D? Evidence from France using propensity score methods on non experimental data. *Revue d'Economique Politique, 114* (2), 263–292.

Ebersberger, B. (2004). Labor demand effects of public R&D funding. *VTT Working Papers* 9. http://www.vtt.fi/inf/pdf/workingpapers/2004/W9.pdf.

Ebersberger, B. (2005). *The impact of public R&D funding*. Espoo, Finland: VTT.

Ebersberger, B. & Lehtoranta, O. (2005). *Pattern of innovative activities among Finnish firms*. Espoo, Finland: VTT.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society, 120,* 11–49u.

Fier, A., Heger, D. & Hussinger, K. (2004). Die Wirkungsanalyse staatlicher Förderprogramme durch den Einsatz von Matching- und Selektionsmodellen am Beispiel der Fertigungstechnik. In: D. Engel (Hrsg.). *Mittelstandsfinanzierung, Basel II und die Wirkung öffentlicher und privater Kapitalbereitstellung.* Berlin.

Griliches, Z. (1998). *R&D and productivity: The econometric evidence*. Chicago: University of Chicago Press.

Haagedorn, J. & Cloodt, M. (2003). Measuring innovative performance: is there an advantage in using multiple indicators? *Research Policy, 32*, 1365–1379.

Hall, B. H. (2005). *Government Policy for Innovation in Latin America*.

Hussinger, K. (2008). R&D and Subsidies at the Firm Level: An Application of Parametric and Semi-Parametric Two-Step Selection Models. *Journal of Applied Econometrics* (forthcoming).

Lach, S. (2002). Do R&D subsidies stimulate or displace private R&D? Evidence from Israel. *Journal of Industrial Economics, 50* (3), 369–390.

Laursen, K. & Salter, A. J. (2006). Open for Innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal, 27* (2), 131–150.

Licht, G. & Stadler, M. (2003). Auswirkungen öffentlicher Forschungsförderung auf die private F&E-Tätigkeit: Eine mikroökonometrische Evaluation. *University of Tübingen Discussion Paper* (256).

Nelson, R. R. (1959). The simple economics of basic scientific research. *Journal of Political Economy, 67,* 297–306.

Ray, S. C. (2004). *Data envelopment analysis* (1. publ.). Cambridge u.a.: Cambridge Univ. Press (theory and techniques for economics and operations research).

Reinowski, E. (2006). Mikroökonometrische Evaluation und das Selektionsproblem – Ein anwendungsorientierter Überblick über nichtparametrische Lösungsverfahren. *Zeitschrift für Evaluation* (2), 187–226.

Rosenbaum, P. R. & Rubin, D. (1983). The central role of the propensity score in observational studie for causal effects. *Biometrika, 70,* 41–55.

Rosenbaum, P. R. & Rubin, D. (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association, 79,* 516–524.

Rubin, D. (1977). Assignment to treatment group on the basis of a covariate. *Journal of Educational Statistics, 2,* 1–26.

Scherer, F. M. & Harhoff, D. (2000). Technology policy for a world of skew-distributed outcomes. *Research Policy, 29* (4/5), 559–566.

Schmidt, T. & Aerts, K. (2006) Two for the price of one: On Additionality Effects of R&D Subsidies: A Comparison Between Flanders and Germany. *ZEW Discussion Papers* (06-063).

Toivanen, O. & Niininen, P. (2000). Investment, R&D, subsidies and credit constraints. *Helsinki School of Economics Workong Papers* (264).

van den Broek, J. & Meussen, W. (1977). Efficiency Estimation from Cobb- Douglas Production Functions with Composed Error. *International Economic Review, 18,* 435–444.

Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: The case of the small business innovation research program. *RAND Journal of Economics, 31* (1), 82–100.

Appendix A: Correlation between key variables in the analysis

Table A1.

		1	2	3	4	5	6	7	8	9	10
1	Innovation expenditure	1.000									
2	Patent application	0.034	1.000								
3	Number of pat. appl.	0.094	0.413	1.000							
4	Pat appl. / R&D empl.	-0.006	0.629	0.444	1.000						
5	Size (log employees)	0.197	0.232	0.227	0.000	1.000					
6	Export intensity	0.075	0.122	0.084	0.036	0.041	1.000				
7	R&D department	0.047	0.263	0.114	0.167	0.197	0.106	1.000			
8	Patent stock	0.034	0.448	0.251	0.230	0.328	0.104	0.283	1.000		
9	Public support	0.090	0.328	0.210	0.223	0.229	0.157	0.337	0.347	1.000	
10	Collaboration for innovation	0.080	0.242	0.142	0.158	0.206	0.073	0.272	0.184	0.277	1.000

The aim of this research is to investigate the incentive effects of the funding instruments of the Finnish Funding Agency for Technology and Innovation (Tekes). The data basis for this analysis is the forth wave of the Community Innovation Survey covering the years 2002 to 2004. In addition the analysis uses the database on business subsidies maintained by the research lab of Statistics Finland. The database includes information on public direct business subsidies and loans at the firm level for years 2000–2005. In also includes the business subsidies and loans granted and paid by Tekes.

The results based on the microeconometric propensity score matching technique show that the public R&D funding has a significant positive effect on the innovation inputs, innovation outputs and on the collaboration breadth and depth of the funded companies. The stochastic frontier analysis reveals that the public R&D funding reduces the inefficiency of the innovation production process. The input into the innovation process is captured by the innovation expenditures. The innovation output is proxied by the number of patent applications.

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