Public Support to Research and Innovation: Do European Resources Boost Innovation Outputs?*

*Vladimír Baláž, Tomáš Jeck***

Abstract

The paper analyses the financial indicators of 546 Slovak firms that received support from the European Structural and Cohesion Funds (ESCF) in the period of 2013–2015. Two support schemes were analysed: one for innovations (technology transfer) and another for R&D grants. The research combines data from public and private resources. It applies the difference-in-differences (DiD) evaluation method along with the propensity score matching (PSM) technique. The research tests the hypotheses that (i) assistance from the ESCF improved the economic and innovation performance of the supported firms, and (ii) smaller firms transformed public support into innovation outputs more efficiently than did large enterprises. Both hypotheses are confirmed. The finding comes with some reservations concerning the efficiency of the support, grant-seeking behaviour, and the reliability of output indicators.

Keywords:: Research and Innovation, Firm Performance, Output Additionality, Difference-in-Differences
JEL Codes: C31; D22; O38.

Introduction

There are many barriers to research and innovation (R&I) in the private sector. There is substantial uncertainty surrounding future trends in technological and product development, as well as uncertainty associated with the profitability of R&I projects (Zemplinerová/Hromádková, 2012: 498). Some firms understand the importance of R&I but have to cope with short-term problems such as genuine credit constraints and/or sudden changes in business cycles.

Public support for private R&I addresses the abovementioned market failures via direct and indirect support for private firms. Direct support mostly takes the forms of grants, subsidies and loans. Meanwhile, tax reliefs and tax deductions are the main forms of indirect support. The ultimate goal of public assistance to R&I is to improve the competitiveness of companies. Such competitiveness, in turn, should be reflected in the improved financial and innovation performance of supported firms (e.g. increase in sales and profitability, development of new products and services, increase in patenting). The size of public support for

* Received: 18.09.2020, accepted: 02.06.2021, 1 revision.

** *Vladimír Baláž*, Research Professor, Institute for Forecasting, Centre of Social and Psychological Sciences, Slovak Academy of Sciences. Email: vbalaz@yahoo.com. Main research interests: intersection of innovation policies, knowledge management, risk research, behavioural economics.
Tomáš Jeck, Senior researcher, PhD. Institute of Economic Research, Slovak Academy of Sciences. Email: tomas.jeck@savba.sk. Main research interests: innovation, knowledge-based economy.

 DOI: 10.5771/0949-6181-2022-1-106

R&I is considerable. The European Structural and Cohesion Funds (ESCF), for example, supported firm-oriented R&I with €30,073.82m in the programming period of 2007–2013/15[1] (EC, 2020[2]). Evidence on the impact of support upon improved firm performance, however, is inconclusive. Studies on the effects of R&I policy interventions often bring contradictory results.

This paper analyses the economic and intellectual property rights (IPR) indicators of 106 research and 440 innovation-intensive Slovak firms that received support from the ESCF in the period of 2013–2015. The paper combines data from public and private resources. The difference-in-differences (DiD) evaluation method along with the propensity score matching (PSM) estimation strategy are applied in order to identify the effects of public support upon firms' economic outcomes (sales, assets, value added, equity, and profits) and IPR (patents and designs) applications.

The novel features of this paper include: (a) relevance – the research evaluates a substantial part of the total EU assistance to Slovak R&I in the programming period of 2007–2013; (b) an evaluation of two different schemes – one focused on R&D and another on innovations; (c) the inclusion of a high number of economic and IPR indicators for measuring output additionality; and (d) an analysis of the efficiency and effectiveness of the support ('value for taxpayer').

1 Literature review

The literature was identified primarily on the basis of searches on Scopus and Google Scholar pages for various keywords (e.g. "R&D investment, innovation support" AND "firm performance/innovation output; efficiency"). Sample sizes and structures, a target population of firms, and research methods were of primary interest. Table 1 summarises the findings from some highly cited studies on public support for R&I and the performance of supported firms.

Literature on the effects of public support upon private R&I falls within three major areas.

(1) The majority of studies concentrate on R&D rather than on innovation-oriented policy measures. The focus on R&D interventions determined the choice of performance category. Input additionality (increase in a firm's own resources for R&D) has been the prime target of the study. The traditional stream of evaluation supported the view that public support crowds out private resources and, therefore, is inefficient (Lokshin/Mohnen, 2013;

1 All contracts concluded in the 2007–2013 programming period had to finish by 2015.

2 Refers to priority themes 'Assistance to R&TD, particularly in SMEs' (€6,085.78m), 'Investment in firms directly linked to research and innovation' (€11,319.81m), 'Other measures to stimulate research and innovation and entrepreneurship in SMEs' (€8,322.15m), and 'Technology transfers' (€4,346.08m).

Wallsten, 2000). More recent meta-analyses pointed to the complexity of evaluating the effects of public support for R&D and found that public subsidies are complementary and, thus, 'add' to private R&D investment (Czarnitzki/Lopes-Bento, 2013; Zúñiga-Vicente et al., 2014; Becker, 2015).

(2) Studies on behavioural additionality focus on behavioural changes at the firm level, such as changes in management and organisation, cooperation with other R&I actors, and changes in the structure of R&I expenditure (Afcha, 2011; Wanzenboeck et al., 2013).

(3) Studies on output additionality consider the direct and indirect impacts of public interventions upon firms' innovative activities and economic outcomes. The direct impacts include changes in innovative activities, such as the production of IPR and/or the introduction of innovative products or process innovations. Meanwhile, the indirect impacts manifest in increased sales, profits, employment, etc. Evaluation studies bring contradictory evidence on the effects of public support for R&I upon innovation outputs (Literature review, Table 1). Some studies found a positive impact on patenting (Aguiar/Gagnepain, 2017; Azoulay et al., 2019; Bronzini/Piselli, 2016; Cappelen et al., 2012; Kaiser/Kuhn, 2012; Merito et al., 2010), labour productivity (Aguiar/Gagnepain, 2017), profitability (Bayona-Sáey/García-Marco, 2010), sales and employment (Benavente et al., 2007), and the development of new products (Foreman-Peck, 2012; Hewitt-Dundas/Roper, 2010). Meanwhile, other studies found no effect or a mixed effect on patenting (Cappelen et al., 2007; Benavente et al., 2007), new products and services (Benavente et al., 2007; Zemplinerová/Hromádková, 2012), sales, assets, and labour productivity (Fantino and Cannone, 2013; Hujer/Radić, 2005; Kaiser/Kuhn, 2012; Karhunnen/Houvari, 2015; Merito et al., 2010). The abovementioned meta-analyses and individual evaluations indicate the complex relationship between public support for private R&I and innovation outputs. The effects of public support upon output additionality can be moderated by a beneficiary's size and/or R&I intensity. Some large-scale evaluations, for example, found that the effects of support are higher for smaller and less productive firms (Vanino et al., 2019) and for firms with lower R&D intensity (Květoň/Horák, 2018; Vanino et al., 2019; Nilsen et al., 2020).

Output additionality received much less attention than did input additionality. A recent literature review on the impact and effectiveness of governmental support for R&D and innovation (Petrin, 2018) found 226 studies on input additionality, albeit only 51 on output additionality. This is rather surprising. The ultimate goal of public support for R&I is to increase the economic and social benefits of innovation. Moreover, studies on innovation outputs show substantial variation in output variables and estimation strategies. The number of patents was the most common indicator of output additionality. Studies on the increase in value added, sales or profits are less common. Relatively few studies analysed several output variables at once.

Findings on outputs can be moderated using an estimation strategy. The results of an evaluation can be biased by the type of estimation strategy and the selection of observable factors for the matching process. The selection of a specific causal inference method is guided by the task structure and the data availability. Various estimation strategies were applied in order to analyse the impacts of the public subsidies upon R&I outputs. DiD with PSM and the Crépon–Duguet–Mairesse model (CDM model) were the most popular methods, followed by the regression discontinuity design (RDD) and ordinary least squares (OLS) with instrumental variables (IV).

Each estimation strategy has its strengths and weaknesses. The CDM model is a structural model which links R&D and innovation investments to R&I outputs. Data on innovation investments usually are available for specific samples of firms, such as those participating in the EU's Community Innovation Surveys (CIS). The CDM model, consequently, was adopted by a number of papers using CIS data (Lööf et al., 2017; Cappelen et al., 2012; Zemplinerová/Hromádková, 2012). The CDM model relies on predefined samples and is less suitable for the evaluation of specific policy measures. The IV method identifies a causal effect via the isolation of an exogenous component (instrument) in the treatment assignment (Hewitt-Dundas/Roper, 2010; Aguiar/Gagnepain, 2017; Azoulay et al., 2019). The instrument impacts the outcome variable only through the endogenous treatment variable. The relationship between the instrument and the treatment variable must be meaningful and strong. Meaningful instruments are not easy to find. The RDD compares two groups that are very similar, except for the treatment (which happens discontinuously on some cut-off). The majority of funding schemes apply scores in order to distinguish supported firms from unsupported ones (Bronzini/Piselli, 2016). In an ideal situation, data are available on scores achieved by firms above and below the cut-off. Meanwhile, the other option is to compare firm performance before and after major changes in policy rules (e.g. eligibility for R&D tax subsidies; Dechezleprêtre et al., 2016). The RDD is less demanding on data than is DiD, but does not include a control group.

Recent large-scale meta-analyses of the impact and effectiveness of public support for R&D and innovation (CLEG, 2015; Petrin, 2018; Květoň/Horák, 2018; Vanino et al., 2019) indicate that DiD with PSM became the preferred technique of evaluation. It enables a more reliable evaluation of the causal effect and addresses the potential bias associated with the 'selection on unobservables'. Hujer/Radić (2005: 583) note that 'the more observable and unobservable factors one takes into account in order to make treated and control establishments more comparable, i.e. the better our understanding of the sample selection process, the smaller the estimated treatment effect of subsidies on innovations becomes'. Our literature review seems to confirm this assumption. Studies based on DiD with PSM generated more conservative results and were more likely to report no effect or a mixed effect of public support upon innovation outputs.

The literature review indicates a research gap. The majority of studies concentrate on input additionality. Output additionality is rather underresearched. Few studies applied DiD with PSM in order to examine the effects of public support for R&I upon several output variables. Only one study (Fantino/Cannone, 2013) targeted the ESCF. Few studies quantify the effectiveness of transforming R&I inputs into innovation outputs. Furthermore, the effectiveness of the support ('value for taxpayer') is rarely discussed in studies on output additionality. We address the research gap and apply DiD with PSM so as to establish the effects of the ESCF upon output additionality by Slovak SMEs.

Chapter Two of the paper presents the data sources, the data structure, and the choice of estimation strategy. Chapter Three presents the key findings on the effects of assistance from European resources upon the competitiveness of Slovak firms. Chapter Four discusses the efficiency of public support to R&D and its 'value for taxpayer'. The concluding part of the paper briefly summarises the major findings and discusses some data limitations. The same chapter also indicates directions for further research.

Table 1: Literature survey on effects of R&I subsidies upon output additionality – selected papers.

Authors	*Research focus*	*Period*	*Sample*	*Estimation method*	*Key findings*
Aguiar/ Gagnepain (2017)	Industry-oriented research joint ventures supported by the FP5.	1998–2002	961 firms	2SLS-IV regression	Increase in labour productivity by, at least, 44.4 % in the long-term.
Azoulay et al (2019)	Impact of scientific grant funding on patenting by pharmaceutical and biotechnology firms.	1980–2005	14,085 projects	OLS FE, IV	NIH funding spurs the development of private-sector patents: a $10 million boost in NIH funding leads to a net increase of 2.7 patents.
Bayona-Sáey/García-Marco (2010)	Economic performance of firms participating in Eureka projects.	1994–2003	866 firms, of which 284 fin Eureka	dynamic unbalanced panel data models (GMM)	Participation had a positive influence on firm's return over assets (ROA).
Benavente et al (2007)	Effects of R&D subsidies on innovation performance by Chilean firms.	1992–2002	219 treated + 220 control firms	DiD with PSM	Increases in sales, employment and export. No significant increase in productivity, patenting and introduction of new products.

Authors	*Research focus*	*Period*	*Sample*	*Estimation method*	*Key findings*
Bronzini/ Piselli (2016)	Impact of R&D subsidies on innovation by Italian firms.	2005–2011	379 treated + 178 control firms	RDD and DiD	Significant impact on the number of patents, more markedly in the case of smaller firms.
Cappelen et al (2012)	Effects of the Norwegian tax credit scheme on the likelihood of innovating and patenting.	1999–2004	1,689 firms	CDM and control function.	Positive effect on new production processed, no significant effect on new products and patenting.
Dechezleprêtre et al (2016)	Effects of change in eligibility for R&D tax subsidies on R&D spending and patenting.	2006–2011	5,888 firms	RDD	Statistically significant increase in patenting and R&D spending.
Fantino/ Cannone (2013)	Effects of ESCF (A) loans and (B) grants on innovation performance by the Italian SMEs.	1999–2008	(A) 212; (B) 139 treated firms.	DiD with PSM	Positive impact on tangible investment; mixed or no effect on sales and assets..
Foreman-Peck (2012)	Impact of UK state aid upon innovation by SMEs.	2002–2004	10,547 UK SMEs	Matching with PSM, OLS and IV	Supported SMEs were more likely to innovate than unsupported comparable enterprises.
Hewitt-Dundas/Roper (2010)	Impact of R&I grants on development of new products in Irish manufacturing plants.	2002–2004	1,681 firms	IV probit estimation	Supported plans developed more new products.
Hujer and Radić (2005)	Effect of public R&D support on innovative activities of German firms.	1997–2001	492 treated + 2222 control firms	DiD with PSM	Average treatment effect was insignificant, except for SMEs (weak positive effect on introduction of new products and services).
Kaiser/Kuhn (2012)	Danish innovation consortia.	1990–2007	217 treated + 173 control firms	DiD with PSM	Increase in patenting, no effect on value added and labour productivity.
Karhunnen/ Houvari (2015)	Effect of R&D subsidies on labour productivity in the Finnish SMEs.	2000–2012	1,221 treated + 1874 control firms	DiD with PSM	No significant positive effect on labour productivity over the five-year period after a subsidy is granted.
Květoň/ Horák (2018)	Effect of public R&D subsidies on assets, sales and profits of Czech firms	2007–2014	345 treated + 2596 control firms	DID with PSM	R&D support had a higher net effect on companies operating (i) in regions with lower R&D intensity, and (ii) mid-tech sectors.

Authors	*Research focus*	*Period*	*Sample*	*Estimation method*	*Key findings*
Nilsen et al (2020)	Effects of direct and indirect support to R&D on performance of Norwegian firms.	2002–2013	1,145 R&D starters + 3,345 R&D/experiences treated versus 68,930 + 2,954 control firms	Dose response function	Positive effects on value added and employment, but mostly in R&D starters.
Vanino et al (2019)	Effects of R&D grants on performance of British firms	2004–2016	5,662 treated + 5,662 control firms	DID with PSM	Positive effect on the employment and turnover growth
Zemplinerová / Hromádková (2012)	Major determinants of innovation activity among Czech companies.	2004–2007	1,069 innovating + 1,002 non-innovating firms4	4-stage CDM model	Significant increases in innovation inputs, but access to subsidies has significant, yet negative influence on innovation output.

Notes: 2SLS-IV = two-stage least squares with instrumental variable; CDM model = Crépon–Duguet–Mairesse model; DiD = difference-in-differences; FE = fixed effects; GMM = generalised moments method; IV = instrumental variable; OLS = ordinary least squares; PSM = propensity score matching; SF = Structural Funds; SMEs = small and medium-sized enterprises.

2 Data sources, data preparation, and estimation strategy

2.1 Data sources and data preparation

Three major datasets were used to construct the treatment and control groups:

- The first dataset was extracted from the National Strategic Reference Framework (NSRF) database. The database is publicly available (DataCentrum, 2021). The database contains data on all projects supported by the ESCF. We extracted data on firms and projects receiving support from three operational programmes: like in other new member countries of the EU (Štreimikienė, 2014), the ESCF were the major source of support for R&I in Slovakia. R&D projects were supported by the Operational Programme Research and Development (OPRD, Policy Measures 2.2 and 4.2) and the Operational Programme Competitiveness and Economic Growth (OPCEG, Policy Measure 1.3). Support was provided via grants for applied research and experimental development. Some 120 firms received €207.42m in assistance from these programmes. The innovation grants co-financed technology transfer and were supported by the OPCEG (Policy Measure 1.1) and the Operational Programme Bratislava Region (OPBR, Policy Measure 2.1). Some 937 firms received €495.56m in support from these programmes.
- The second dataset was extracted from the FinStat database. The database is managed by a private company. It contains data on the annual accounts and

financial statements of all Slovak Ltd. and PLC-type companies. The authors purchased access to the database.

- The third dataset on patents and designs was extracted from a database managed by the Industrial Property Office of the Slovak Republic (IPOSR). Patents and designs are the most common IPR registered with Slovak companies. The database is publicly available (IPOSR, 2021).

We compared economic and IPR data for the treatment group with data for firms receiving no support (control group). The NSRF database provided data on firms in the treatment group. Firms in the control and treatment groups were paired with firms applying for patents and designs in the period of 2012–2018. The FinStat and IPOSR databases provided data on output performance variables in the treatment and control groups.

Historical economic data are not available for the majority of Slovak companies. The FinStat database includes a sample of 143,701 companies whose annual accounts are available from 2012[3]. The sample partly overlaps with the list of 120 + 937 Slovak firms receiving R&D and innovation grants. Complete financial data were available for 40,895 firms in the period of 2012–2018. Supported firms differed from unsupported ones in several aspects. The vast majority of the Slovak firms were microenterprises with annual sales well below €1m in 2012. The median 2012 sales constituted €0.183m for unsupported firms but €1.316m for firms receiving innovation grants, as well as €2.445m for firms receiving R&D grants. We excluded companies from the control group with sales below €0.25m or above €100.0m so as to eliminate the outliers. The support schemes required that applicants prove their financial health. The applicants had to report six financial indicators, of which equity and profitability accounted for 88.3 % of the score. We further excluded firms with negative and/or zero equity from the FinStat database. Finally, we also excluded telecommunications, utility monopolies, and all multinational companies from the control sample. The final donor pool constituted 33,877 firms, of which 106 firms received R&D grants and 440 firms received innovation grants. A sample of 106 R&D firms received €189.61m in funding (91.41 % of the total budget of the scheme). Meanwhile, a sample of 440 innovating firms received €385.86m in funding (77.86 % of the total budget of the scheme).

We ensured that further analysis would capture the relevant part of the support schemes, despite extensive data cleaning.

3 Financial data are patchy for the period prior to 2012. We were unable to compute annual averages for financial data prior to 2012.

2.2 Estimation strategy

The CDM model and RDD and IV methods have some advantages when data on control and treatment groups in the pre-treatment and post-treatment periods are not available. The CDM model was not applicable to this study, as we lacked data on the R&I inputs. DiD includes a control group and is generally more robust against confounders than is the RDD. Moreover, we lacked data on the scores of supported and unsupported firms. This research benefitted from large datasets of treated and untreated firms. The firm-level data were available for both the pre- and the post-treatment periods. Therefore, DiD was the prime choice for the analysis.

DiD attempts to mimic an experimental research design through the use of observational study data. It calculates the effect of a treatment variable (i.e. an explanatory or independent variable) upon an outcome (i.e. a response or dependent variable) by comparing the average change over time in the outcome variable for the treatment group to the average change over time for the control group. There is a rather strong assumption that firms in control and treatment groups do not differ in the most important aspects, such as size, industry sector, technology intensity, ownership, etc. Such an assumption sometimes is difficult to prove. Specific industries account for different profit rates, shares of university-educated workers and/or research and innovation intensities. There is an option to use some statistical techniques, such as PSM, and match each agent from the treatment group with a 'mirror agent' from the control group (for further details on the 'matching design', see Pearl (2009)). PSM increases the comparability of the treatment and control groups in respect of the observable variables.

We have used the PSM technique to create samples of treated and control firms. The most important output variables included sales, assets, equity, value added, profits, and patent and design applications. The development of output additionality for supported/unsupported firms between the periods of 2012 and 2016–2018 was compared via the t-test.

2.3 Research hypotheses

Slovak firms supported by the ESCF do not provide data on their past R&I expenditure. It is therefore impossible to determine whether the Structural Fund interventions contributed to an increase in business expenditure on R&I.

We investigate the effects of substantial interventions (€575.47m) upon the economic and innovation performance of Slovak SMEs. Improved competitiveness is the ultimate goal of public support for research and innovation. Significant effects are expected, given the size of the intervention.

Two hypotheses are proposed:

H1: Assistance from the ESCF improved the economic and innovation performance of the supported firms.

H2: Smaller firms (i.e. those with lower assets, sales and equity) improved their performance more than did larger ones.

2.4 Matching procedure

The DiD method is based on (i) definition of the appropriate time period, (ii) selection of the appropriate variables, and (iii) construction of the treatment and control groups.

Time periods

The choice of periods was guided by the spending cycle and the availability of data on output variables. Two periods were chosen to compare the development of economic efficiency in the treatment and control groups over time: 2012 (pre-intervention period) and 2016–2018[4]. The intervention period included the years 2013–2015. The first calls for innovation and R&D projects were launched in 2008, but spending was rather slow. The four Policy Measures disbursed 29.8 % of their total budget by the end of 2012. Economic effects from projects concluded in 2012, for example, appeared in the firms' 2013 annual accounts. The period of 2013–2015 is therefore considered the intervention period[5].

Output variables

Output additionality is measured via improvement in economic and IPR performance. The selection of economic variables reflected their economic importance and their availability in the FinStat database. The economic variables included assets, sales equity, value added, and gross operating surplus (profit) (Appendix, Table 4). The choice of IPR variables was guided by the national economic and business environment. Slovakia accounts for a low intensity of EPO and USPTO applications. EPO and USPTO applications are quite expensive and seldom filled in by Slovak firms. National patent and design applications with the IPOSR were selected as the IPR variables. Designs are more numerous and more typical for business-oriented innovations than are patents. We did not

4 Period averages were used to smooth annual fluctuations from 2016 to 2018. As for the pre-intervention period, data were available only for 2012.

5 The effects of projects supported in the 2007–2013/15 programming period did not interfere with the potential effects of projects supported in the 2014–2020 programming period. The latter programming period accounted for an even slower spending cycle than that of the former one. A mere 87 firms were supported with some €56.8m (14.0 % of the R&I allocations) by the end of 2018.

include trademarks, as they need not necessarily refer to research and innovation activities.

Construction of treatment and control groups with PSM

Firms receiving support from the four ESCF schemes may differ from the non-participating firms. Participating firms are likely to be more technology-intensive and constitute a higher share of PLC-type companies. If one, for example, were to compare firms with and without support from the ESCF, the comparison would likely generate biased results. PSM was used to create comparable structures of the treatment and control groups. PSM attempts to reduce the bias due to confounding variables that could be found in an estimate of the treatment effect obtained from simply comparing outcomes among units that have received the treatment and those that have not. What is more, the PSM method attempts to find a 'mirror member' in the control group in relation to each member in the treatment group. A propensity score allows one to design and analyse an observational (nonrandomised) study so that it mimics some of the particular characteristics of a randomised controlled trial.

A standard logit model is used to estimate the propensity scores. The binary dependent variable denotes whether or not a firm participated in the support programme. The propensity scores are saved and used for construction of the treatment and control groups. Caliper matching with the maximum acceptable distance between propensity scores is applied in order to find the best matching between members of the treatment and control groups. A tighter caliper reduces bias and results in closer matches, but some members of the treatment group could not be matched. Calipers with a width of up to 0.2 of the standard deviation of the logit of the propensity scores were suggested for the PSM procedure (Austin, 2011). We had a large control group sample and opted for tighter matching with a caliper of 0.1.

Propensity scores were tested in two steps. The first step included the most common control variables for observable characteristics, such as firm age, firm size, and sector of business (CLEG, 2015: 21). The following variables were tested for inclusion in the PSM score:

- *Firm age*. The age was set in years from a firm's establishment until 2012. Firm age is a proxy for accumulated knowledge and managerial skills (Walsten, 2000; Merito et al., 2010).
- *Ownership type*. Three ownership types were established. Type 1 constituted domestic ownership, type 2 international ownership, and type 3 foreign ownership. Foreign ownership and international ownership are proxies for access to international tacit knowledge.

- *Legal form.* Three forms were established. Form 1 constituted a limited liability company, form 2 a cooperative, and form 3 a PLC-type or similar company. Legal form is a proxy for access to financial and human capital.
- *Technology intensity*. Intensity was defined by the Eurostat indicators of High-tech industry and Knowledge-intensive services[6]: level 1 constituted low-technology manufacturing industries and less knowledge-intensive services; level 2 constituted medium-low and medium-high manufacturing industries, as well as knowledge-intensive services (excluding high-technology knowledge-intensive services); and level 3 constituted high-technology manufacturing industries and high-technology knowledge-intensive services. Technology intensity was a proxy for a firm's potential in the production of IPR.
- *Firm size.* EU recommendation 2003/61 defines firm size by the amount of employees and/or turnover. Data on employees were available for the selected firms only. We used turnover for defining firm size. As with legal form, firm size was a proxy for access to financial and human capital.

The first ('naive') DiD did not generate satisfactory results. Firms in the control sample accounted for substantial volatility in sales, assets and profits. Standard deviations of covariates were quite high. The tight caliper of 0.1 was not sufficient to produce balanced samples of treated and untreated firms. DiD with PSM assumes that different behaviour by treatment and control groups is generated solely by the policy interventions and/or the observable variables, and there are no unobservable variables in play. An estimation of causal effects has to identify variables that affect both selection into treatment and the outcomes of the intervention. The same firms, for example, may have participated in past support schemes and/or been patent-active prior to the intervention. Previous experience with public support may enhance the probability of participation in the current intervention (Kaiser and Kuhn, 2012: 922). We therefore identify 'frequent users' of public support programmes so as to control for the potential self-selection of firms for the policy intervention. The following variables were chosen to mitigate the effects of unobservable variables in the second step of the logit model:

- History of participation in the ESCF schemes developed in the previous programming period of 2006–2008. The binary variable denoted participation in the SOPIS 1.3 DM, SOPIS 1.3 SA and SOPIS 1.4 Policy Measures[7];
- History of participation in the FP7 projects (binary variable);

6 Eurostat indicators of High-tech industry and Knowledge-intensive services Annex 3 – High-tech aggregation by NACE Rev.2.

7 SOPIS stands for Sectoral Operational Programme Industry and Services. The SOPIS 1.3 DM Policy Measure supported small (*de minimis*) projects on innovation in 2004–2006. The SOPIS 1.3 SA Policy Measure allocated state aid to R&I projects. The SOPIS 1.4 Policy Measure supported process innovations and technology transfer.

- History of participation in the national programmes of the Slovak Research and Development Agency (RDA, binary variable);
- State R&D stimuli awarded in the period of 2009–2012.

The second step of the logit model produced more balanced samples of treated and untreated firms. In an ideal case there should be no statistically significant differences between the treatment and control groups in the pre-treatment period (2012). The supported firms used to have somewhat higher sales, value added, and profits. Some differences were significant, but some not. As for the IPR indicators, there were no statistically significant differences between firms in the treatment and control groups in the pre-treatment period[8].

PSM generated a sample of 440 firms in the treatment group and 438 firms in the control group for innovation grants (Appendix, Table 4). As for the R&D grants, the treatment group included 106 firms, while the control group constituted 100 firms. Descriptive statistics on economic indicators (sales, assets, equity, profits, ROA and ROE) and IPR indicators (patents and designs) are reported in Appendix, Table 4. The logit model is presented in Appendix, Table 5.

3 Output additionality

The key results for output additionality are presented in Table 2. All indicators of sales, assets, equity, profits, ROA and ROE, as well as IPR, refer to changes in the period of 2016–2018 in comparison to 2012.

3.1 Innovation grants

OPCEG Policy Measure 1.1 and OPBR Policy Measure 2.1 supported technology transfer and a targeted increase in competitiveness and value added. An increase in the IPR outputs was a less important target.

The supported firms increased their assets, sales, equity, value added, and ROA ratio significantly more than did the unsupported ones in 2016–2018 in comparison to 2012. The finding confirms Hypothesis 1. These increases were statistically significant on a 0.05 – 0.001 level (Table 2). Firms in the control group accounted for higher variability in equity and profits. The ROE ratio has a high standard deviation and is unreliable for the control group.

The supported firms increased the numbers of their patent applications more than did the unsupported ones. The numbers of design applications decreased for both supported and unsupported firms. None of these changes in IPR intensity were significant at the 0.05 level.

8 We experimented with using a tighter caliper (0.05) to match the samples. The tight caliper substantially reduced the control group.

3.2 *R&D grants*

OPCEG Policy Measures 2.2 and 4.2 supported applied and industry-oriented research. The amount of IPR was the key indicator in output additionality[9].

The supported firms accounted for higher absolute increases in sales, equity, and value added than did the unsupported ones. Differences were statistically significant at the 0.01 level for sales and value added (Table 2). As for IPR, average annual numbers of patent and design applications actually decreased in 2016–2018 (in comparison to 2012) in both the treatment and the control groups. The difference in the change in patent and design intensity between the treatment and control groups was not statistically significant.

Literature reviews on output additionality (CLEG, 2015; Petrin, 2018; Vanino et al., 2019) find that public support matters more to SMEs than to large firms. The Slovak firms receiving R&D grants were (on average) 2.7 times greater than firms receiving innovation grants in terms of assets, sales and equity in 2012 (Appendix, Table 4). The supported firms reported relatively lower and statistically insignificant increases in equity and value added in comparison to the unsupported ones by 2016–2018. The finding confirms Hypothesis 2.

9 Both policy measures set input additionality indicators, such as new jobs for researchers, and some behavioural additionality indicators (number of public–private partnerships, introduction of innovation management programmes, and mobility of researchers between industry and academia sectors). The input and behavioural additionalities are outside of the scope of this paper.

Table 2: Financial and IPR indicators for firms receiving/not receiving support from the ESCF and CF. Differences between 2016–2018 and 2012.

			Mean change	*Std. dev.*	*t*	*sig.*		*Mean change*	*Std. dev.*	*T*	*sig.*
Indicator	*support*	*N*	**innovation grants**				*N*	**R&D grants**			
assets	no	438	0.356	9.805	-1.922	**0.047**	100	2.905	15.581	1.555	0.123
	yes	440	1.344	3.391			106	0.401	4.192		
sales	no	438	-1.765	9.567	-5.745	**0.000**	100	-1.434	5.057	-2.700	**0.008**
	yes	440	0.971	2.789			106	1.415	9.336		
equity	no	438	-0.102	2.951	-2.833	**0.005**	100	0.590	5.287	0.801	0.455
	yes	440	0.328	1.171			106	0.173	2.147		
value added	No	438	-0.544	2.434	-7.936	**0.000**	100	-0.740	1.376	-2.712	**0.007**
	yes	440	0.428	0.810			106	1.211	7.065		
profits	no	438	-0.241	1.149	-3.377	**0.000**	100	-0.289	1.164	-1.584	0.115
	yes	440	-0.018	0.360			106	-0.022	1.249		
ROA	no	438	-0.195	0.797	-4.202	**0.000**	100	-0.202	1.205	-1.018	0.310
	yes	440	-0.033	0.118			106	-0.078	0.346		
ROE	no	438	6.606	158.901	0.911	0.363	100	0.681	10.296	0.842	0.402
	yes	440	-0.308	2.236			106	-0.189	0.854		
patents	no	438	0.002	0.033	-0.464	0.643	100	-0.026	0.188	1.304	0.194
	yes	440	0.003	0.075			106	-0.096	0.519		
designs	no	438	-0.009	0.175	-0.634	0.526	100	-0.037	0.341	0.504	0.615
	yes	440	-0.002	0.144			106	-0.069	0.539		

Source: authors' computations. Notes: St. dev. = standard deviation; sales, assets, equity and profits are reported in €m, and patents and designs in physical units; and ROA and ROE are indices. The t-values and significance levels (two-tailed) are quoted separately for assumptions on equal and unequal variances. Variables significant at the 0.1 level are in bold.

4 Discussion

4.1 Efficiency of public support to R&I: firm type and effect size

Efficiency is concerned with doing things in an optimal way, i.e. transforming inputs into outputs. Vanino et al. (2019: 1716) note that 'the positive effects of public R&D support on private R&D investment and innovation do not necessarily mean that these public programmes enhance productivity and thus eventually contribute to economic growth'. Our research pointed to the same conclusions.

Recipients of the Slovak R&I grants had to match the public subsidy with their own R&I investment. The R&I input additionality, however, did not transfer to output additionality in terms of enhanced productivity. Values of the ROA and ROE indicators, in fact, decreased in 2016–2018 in comparison to 2012.

Table 3 compares the transformation of innovation inputs into outputs for two types of firms: (i) smaller firms with innovation grants, and (ii) larger firms with R&D grants. Smaller firms transformed innovation inputs with somewhat higher efficiency than did larger ones, at least in terms of increases in assets, equity and profits. One euro received via an innovation grant in 2012 was associated with an increase in sales by 1.11 euros in 2016. One euro received via an R&D grant increased sales only by 0.79 euros in the same time period. The larger firms were marginally more efficient only in increasing value added (Table 3).

Our conclusion that larger Slovak firms generally are less efficient in transforming innovation inputs into outputs than are smaller ones resonates with findings by Zemplinerová and Hromádková (2012: 498) on Czech firms. Nilsen et al. (2020: 14) and Vanino et al. (2020: 1732) also point to decreasing returns on higher support for Norwegian and UK firms respectively.

Table 3: Efficiency of public support: transforming inputs into outputs. Innovation outputs (euros) per one euro of public support.

Change in variable 2016 versus 2012	*innovation grant*	*R&D grants*
sales	**1.11**	**0.79**
assets	**1.53**	0.22
equity	**0.37**	0.10
profits	**-0.02**	-0.01
value added	**0.49**	**0.68**

Variables significant at the 0.1 level are in bold.

Reported innovation outputs may account for different degrees of reliability. Supported firms mostly reported better financial health than that of the unsupported ones, both before and after the intervention. Better financial health may refer not only to better management but also to strategic planning. The majority of Slovak firms try to minimise the tax burden via tax optimisation and/or tax avoidance. The FinStat database indicates that no tax liability claimed 52.3 % of Slovak firms in 2013. Firms applying for the R&D and innovation grants had to present their annual accounts to an evaluation committee. Firms deemed to be financially unstable did not qualify for the support. Some applicants ('frequent users' of public support) may have considered grant seeking to be an alternative to tax optimisation. Firms supported by the innovation and R&D grants were more motivated to report profits (and pay some corporate tax) than were the unsupported ones. Data on profits, and on returns on assets and equity, therefore, should be observed with greater care than those on sales.

4.2 *Effectiveness of public support to R&I: value for money?*

Effectiveness is concerned with performing the right task, completing activities and providing the desired result. The right task for public support schemes comprises improving economic performance and increasing the numbers of valuable IPR outputs.

The output indicators must be set to the national economic and business context. An increase in assets need not necessarily relate to higher efficiency. It may result from simple technology transfer sponsored by public grants. The size of the intervention was substantial. Median support accounted for 30.10 % of the 2012 assets of recipients of innovation grants and 43.53 % of the assets of recipients of R&D grants. The innovation grants supported technology transfer. New machinery and equipment boosted the total volume of assets[10]. The amount of support raises questions regarding the sources of output additionality. How much of the increases in sales, assets and equity is due to product, process and organisational innovation and how much to a simple extension of production capacity? Our findings correspond to those by Dvouletý et al. (2019: 12). They found that the increase in tangible fixed assets was the only significant effect of the Czech credit guarantee programme in the period of 2014–2015.

Some reservations concern the effectiveness of the support. Beneficiaries of the R&D grants decreased their average annual number of IPOSR patent applications from 15 in 2012 to five in 2016–2018. We consider five national patent applications supported by R&D grants (€189.61m; €37.92m per patent application) to be poor value for money. Azoulay et al. (2019: 119), for example, found that a $10m boost in US NIH funding led to a net increase of 2.7 USPTO patents. Bronzini and Piselli (2016: 443) showed that one additional EPO patent application required a grant of between €0.206m and €0.310m to an Italian firm.

10 A breakdown of support into fixed assets and wages was not available for the R&D grant scheme.

Furthermore, some reservations may apply to reporting IPR indicators. Patent and design applications were performance indicators stipulated by the scheme rules. We are not able to state how many patent and design applications were reported to satisfy the performance criteria and how many generated genuine economic and social benefits.

5 Conclusions and directions for further research

The research brought two main findings. Hypothesis 1, i.e. *assistance from the ESCF improved the economic and innovation performance of the supported firms*, was confirmed. Our findings on the effects of the ESCF are in line with those by Hujer/Radić (2005), Benavente et al. (2007), Fantino and Cannone (2013) and Butkus et al. (2019). The finding, however, comes with some reservations concerning the efficiency of the support, grant-seeking behaviour, and the reliability of output indicators. Hypothesis 2 suggested that *smaller firms improved their performance more than did larger ones*. The hypothesis was confirmed. Our findings are in line with those by Kaiser and Kuhn (2012), Fantino/Cannone (2013), Zemplinerová/Hromádková (2012), Vanino et al. (2019) and Nilsen et al. (2020), but come with the same reservations as for Hypothesis 1. Low values of transformation coefficients indicate that the efficiency of the transformation was rather low. High costs of national patent applications point to poor value of money. The findings raise doubts as to the overall effectiveness of public support to R&I in Slovakia.

Our research had some important limitations. Financial data were not available for all enterprises in the control and treatment groups prior to 2012. It is impossible to state how the availability of data impacted upon the structure of the control and treatment groups. It can be assumed that the best data were available for medium-sized and large enterprises with a medium-long or long corporate history. Such enterprises are likely to have better financial results than those of small and/or new businesses in both samples. Data constraints limited the length of the pre-intervention period to one year (2012). The FinStat database contained incomplete data on employment. We were unable to compute the effects of ESCF assistance upon labour productivity.

We included a high number of controls in the PSM procedure so as to mitigate the effects of potential unobservable variables. Some unobservables, however, may bias the results. The competitiveness of enterprises may be impacted by a number of factors, such as (1) external factors of sales and costs within specific industries (e.g. prices of inputs), (2) the quality of management in specific businesses, (3) the dependence of an enterprise upon regional transportation infrastructure, and (4) the availability of human resources and other production inputs within a region and/or international markets.

Addressing the abovementioned unobservable variables is an obvious direction for further research. Further research can evaluate the quality of regional transportation infrastructure via its connectivity to the Trans-European Transport Network (TEN-T). The quality of regional universities may be a proxy for the availability and quality of human resources.

This research observed changes in output variables in a period three years after the intervention. Some long-term effects, such as increasing intensity in patenting, may take more time to develop. Meanwhile, another direction for further research is to re-examine the economic and financial indicators of treated and untreated firms after some time. Long-term observations also enable the separation of short-term effects (increase in economic output) from long-term ones (increase in IPR activities).

Last but not least, the costs and benefits of public interventions should attract more attention from researchers. Most research included in the literature review concentrated on the technical aspects of evaluation, such as sample construction, estimation strategies, and the statistical significance of output variables. Our research indicated that it is not enough to show that supported firms accounted for better performance than did unsupported ones. Future research should be more concerned with the efficiency of support and the 'value for taxpayer'. Another stream of research may address strategic planning, tax optimisation, and grant-seeking strategies by firms applying for public support. Business strategies may impact upon self-selection of firms into support schemes and, consequently, the quality of reported output indicators (e.g. profits, value added or the number of patent applications).

Acknowledgment

This research was supported by VEGA grant no. 2/0002/18 and VEGA grant no. 2/0097/19.

References

Afcha, C.S. (2011): Behavioural additionality in the context of regional innovation policy in Spain, in: Innovation-Management Policy & Practice, 13, 1, 95–100.

Aguair, L./Gagnepain, P. (2017): European cooperative R&D and firm performance: Evidence based on funding differences in key actions, in: International Journal of Industrial Organization, 53, C, 1–31.

Austin, P.C. (2011): An introduction to propensity score methods for reducing the effects of confounding in observational studies, in: Multivariate behavioural research, 46, 3, 399–424.

Azoulay, P./Graff Zivin, J.S./Li, D./Sampat, B.N. (2019): Public R&D Investments and Private-sector Patenting: Evidence from NIH Funding Rules, in: The Review of Economic Studies, 86, 1, 117–152.

Bayona-Sáez, C./García-Marco (2010): Assessing the effectiveness of the Eureka Program, in: Research Policy, 39, 10, 1375–1386.

Becker, B. (2015): Public R&D policies and private R&D investment: A survey of the empirical evidence, in: Journal of Economic Surveys, 29, 5, 917–942.

Benavente, J.M., Crespi, G./Maffioli, A. (2007): Public Support to Firm-Level Innovation: An Evaluation of the FONTEC Program, in: Inter-American Development Bank (IDB) Working Paper Series Ove/wp-05/07, 1–23.

Bronzini, R./Piselli, P. (2016): The impact of R&D subsidies on firm innovation, in: Research Policy, 45, 2, 442–457.

Butkus, M./Cibulskiene, D./Mačiulytė-Šniukienė, A./Matuzevičiūtė, K. (2019)" What is the return on investing European Regional Development and Cohesion Funds? Difference-in-differences Estimator Approach, in: Ekonomický časopis, 67, 6, 647–676.

Cappelen, Å./Raknerud, A./Rybalka, M. (2012):The effects of R&D tax credits on patenting and innovations, in: Research Policy, 41, 2, 334–345.

CLEG (2015): What works? Evidence Review 9. Innovation: grants, loans and subsidies, Centre for Local Economic Growth, London, available at, https://whatworksgrowth.org/public/files/Policy_Reviews/15-10-20-Innovation-Grants-Loans-Subsidies-Report.pdf, referred on 01/05/2020.

Czarnitzki, D./Lopes-Bento, C. (2013):Value for money? New microeconometric evidence on public R&D grants in Flanders, in: Research Policy, 42, 1, 76–89.

DataCentrum, (2021): ITMS 2014+ database of ESIF projects, available at: http://www.itms.datacentrum.sk/itms-2014-2020-itms2014/itms2014-verejna-cast-8c.html (last accessed on 21 January 2021).

Dechezleprêtre, A./Einiö, E./Martin, R./Nguyen, K.-T./van Reenen, J. (2016): Do tax incentives increase firm innovation? An RD Design for R&D, in: NBER Working Paper No. 22405, 1–40.

Dvouletý O./Čadil, J./Mirošník, K. (2019): Do Firms Supported by Credit Guarantee Schemes Report Better Financial Results 2 Years After the End of Intervention? In: The B.E. Journal of Economic Analysis & Policy,19, 1, pp. 1–20,

EC, European Commission (2020): European Structural and Investment Fund Data, 007–2013 – Priority theme vs form of finance", available at: https://cohesiondata.ec.europa.eu/2007-2013/2007-2013-Priority-theme-vs-form-of-finance-2014-s/ay75-94kc, referred on 01/05/2020

Fantino, D./Cannone, G. (2013): Evaluating the efficacy of European regional funds for R&D, Temi di discussione (Economic working papers) 902, Bank of Italy: Economic Research and International Relations Area.

Foreman-Peck, J. (2013): Effectiveness and efficiency of SME innovation policy. Effectiveness and efficiency of SME innovation policy, in: Small Business Economics, 41, 1, 55–70.

Hewitt-Dundas, N./Roper, S. (2010): Output Additionality of Public Support for Innovation: Evidence for Irish Manufacturing Plants, in: European Planning Studies, 18, 1, 107–122.

Hujer, R./Radić, D. (2005): Evaluating the Impacts of Subsidies on Innovation Activities in Germany, in: Scottish Journal of Political Economy, Scottish Economic Society, 52, 4, 565–586.

IPOSR, Industrial Property Office of the Slovak Republic (2021), Databases – Patents, available at: https://www.indprop.gov.sk/?databases-patents (last accessed on 21 January 2021).

Kaiser, U./Kuhn, J.M. (2012): Long-run effects of public–private research joint ventures: The case of the Danish Innovation Consortia support scheme, in: Research Policy, 41, 5, 913-927.

Karhunen, H./Houvari, J. (2015): R&D subsidies and productivity in SMEs, in: Small Business Economics, 45, 4, 805–823.

Květoň, V./P. Horák. (2018): The Effect of Public R&D Subsidies on Firms' Competitiveness: Regional and Sectoral Specifics in Emerging Innovation Systems, in: Applied Geography, 94, pp. 119–129.

Lokshin, B./Mohnen, P. (2013): Do R&D tax incentives lead to higher wages for R&D workers? Evidence from the Netherlands, in: Research Policy, 42, 3, 823–830.

Lööf, H./Mairesse. J./Mohnen, P. (2017): CDM 20 years after, in: Economics of Innovation and New Technology, 26, 1–2, 1–5.

Nilsen, Ø. A./ Raknerud, A./Iancu, D.C. (2020): Public R&D support and firm performance: A multivariate dose-response analysis, in: Research Policy, 49, 7, pp. 1–16.

Merito, M./Giannangelli, S./Bonnaccorsi, A. (2010): Do incentives to industrial R&D enhance research productivity and firm growth? Evidence from the Italian case, in: International Journal of Technology Management, 49, 1–3, 25 – 48.

Petrin, T. (2018): A literature review on the impact and effectiveness of government support for R&D and innovation, in: ISIGrowth Working Paper. 1–56

Štreimikienė, D. (2014), "The Impact of Research and Development for Business Innovations in Lithuania", Economic Interferences, Vol. 16, Issue 37, pp. 965–979.

Vanino, E., Roper, S./ Becker, B. (2019): Knowledge to money: Assessing the business performance effects of publicly-funded R&D grant, in: Research Policy, 48, 7, pp. 1714–1737.

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, in: The RAND Journal of Economics, 31, 1, 82–100.

Wanzenboeck, I./Scherngell, T./Fischer, M.M. (2013): How do firm characteristics affect behavioural additionalities of public R&D subsidies? Evidence for the Austrian transport sector, in: Operations Research & Management Science, 33, 2–3, 66–77.

Zemplinerová, A./Hromádková, E. (2012): Determinants of firm's innovation. in: Prague Economic papers, 21, 4, 487–503.

Zúñiga-Vicente, J.Á./Alonso-Borrego, C./Forcadell, F. J./Galán, J.I. (2014): Assessing the effect of public subsidies on firm R&D investment: a survey, in: Journal of Economic Surveys, 28, 1, 36–67.

Appendix

Table 4: Descriptive statistics for financial and IPR indicators for firms receiving/not receiving support from the SF and CF

			Mean	*Std. dev.*	*t*	*sig.*		*Mean*	*Std. dev.*	*t*	*sig.*
indicator	support	*N*	**Innovation grants**				***N***	**R&D grants**			
assets 12	No	438	4.539	8.796	2.419	**0.016**	100	7.365	10.446	-0.963	0.337
	Yes	440	3.301	6.131			106	9.089	14.743		
assets 16–18	No	438	4.896	13.019	0.349	0.728	100	10.270	21.127	0.313	0.755
	Yes	440	4.644	7.631			106	9.490	14.204		
sales12	No	438	2.784	9.809	-0.853	0.395	100	3.186	5.951	-3.040	**0.003**
	Yes	440	3.233	5.093			106	9.803	21.550		
sales 16–18	No	438	1.019	2.776	-10.056	**0.000**	100	1.753	3.311	-3.612	**0.000**
	Yes	440	4.204	6.022			106	11.218	26.762		
equity12	No	438	1.741	5.016	1.145	0.252	100	2.442	4.798	-1.275	0.204
	Yes	440	1.381	4.258			106	3.551	7.341		
equity 16–18	No	438	1.639	5.576	-0.204	0.838	100	3.031	6.990	-0.719	0.473
	Yes	440	1.709	4.507			106	3.724	6.827		
value added 12	No	438	0.493	2.448	-2.953	**0.003**	100	0.551	1.633	-3.046	**0.003**
	Yes	440	0.877	1.195			106	3.717	10.569		
value added 16–18	No	438	-0.051	0.599	-16.224	**0.000**	100	-0.189	0.970	-3.109	**0.002**
	Yes	440	1.305	1.647			106	4.928	16.914		
profit12	No	438	0.218	1.053	1.036	0.301	100	0.274	1.073	-1.499	0.135
	Yes	440	0.163	0.298			106	0.567	1.653		
profit 16–18	No	438	-0.023	0.705	-4.267	**0.000**	100	-0.015	1.134	-2.700	**0.008**
	Yes	440	0.146	0.436			106	0.545	1.787		
ROA 2012	No	438	0.041	0.182	-3.155	**0.002**	100	0.016	0.145	-2.648	**0.009**
	Yes	440	0.072	0.104			106	0.064	0.115		

			Mean	*Std. dev.*	*t*	*sig.*		*Mean*	*Std. dev.*	*t*	*sig.*
ROA 16–18	No	438	-0.154	0.822	-4.892	**0.000**	100	-0.186	1.225	-1.392	0.165
	Yes	440	0.039	0.086			106	-0.014	0.343		
ROE 12	No	438	-6.786	158.757	-0.949	0.344	100	-0.734	10.130	-0.993	0.322
	Yes	440	0.398	2.143			106	0.250	1.177		
ROE 16–18	No	438	-0.179	2.740	-2.011	**0.045**	100	-0.053	1.559	-0.644	0.521
	Yes	440	0.090	0.571			106	0.062	0.876		
patents 12	No	438	0.000	0.000	-0.998	0.318	100	0.050	0.261	-1.481	0.141
	Yes	440	0.002	0.048			106	0.142	0.576		
patents 16–18	No	438	0.002	0.033	-1.127	0.260	100	0.024	0.183	-0.905	0.367
	Yes	440	0.006	0.068			106	0.045	0.154		
designs 12	No	438	0.011	0.172	-0.422	0.673	100	0.060	0.371	-1.131	0.259
	Yes	440	0.016	0.142			106	0.142	0.624		

Source: authors' computations. Notes: St. Dev. = Standard Deviation; Notes: sales, assets, equity and profits are reported in €m, patents and designs in physical units; ROA and ROE are indices. The *t*-values and significance levels (2-tailed) are quoted separately for assumptions on equal and unequal variances. Variables significant on 0.1 level in bold.

Table 5: Logit model for the propensity score matching

intervention	**innovation grants**						**R&D grants**					
variables	*B*	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*B*	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
constant	-6.919	0.278	619.090	1	0.000	0.001	-10.921	0.612	318.941	1	0.000	0.000
ownership	-0.749	0.102	53.924	1	0.000	0.473	-0.359	0.165	4.718	1	0.030	0.699
age	0.053	0.043	1.495	1	0.221	1.054	0.052	0.094	0.309	1	0.578	1.054
firm size	0.633	0.050	158.351	1	0.000	1.884	0.133	0.094	1.983	1	0.159	1.142
assets	0.330	0.053	38.187	1	0.000	1.391	0.694	0.118	34.740	1	0.000	2.001
tech intensity	0.367	0.083	19.736	1	0.000	1.443	0.958	0.163	34.604	1	0.000	2.607
legal form	-0.371	0.088	17.681	1	0.000	0.690	0.104	0.134	0.602	1	0.438	1.110
R&D stimuli	0.008	1.552	0.000	1	0.996	1.008	-2.610	1.408	3.436	1	0.064	0.074
RDA grants	1.039	0.466	4.966	1	0.026	2.825	2.480	0.473	27.454	1	0.000	11.944
FP7	-0.350	0.942	0.138	1	0.710	0.704	2.644	0.550	23.159	1	0.000	14.076
SOPIS 1.3	2.837	0.228	154.529	1	0.000	17.063	2.804	0.320	76.819	1	0.000	16.516
SOPIS 1.4	0.646	0.594	1.183	1	0.277	1.908	1.201	0.672	3.193	1	0.074	3.324
profit	-1.98E-07	0.000	1.556	1	0.212	1.000	-5.75E-08	0.000	0.210	1	0.647	1.000
equity	-3.38E-08	0.000	2.069	1	0.150	1.000	-5.31E-08	0.000	3.522	1	0.061	1.000
value added	-2.67E-07	0.000	16.704	1	0.000	1.000	3.00E-08	0.000	4.978	1	0.026	1.000
patents	-1.115	0.966	1.332	1	0.248	0.328	1.818	0.626	8.445	1	0.004	6.161
designs	0.942	0.402	5.501	1	0.019	2.565	0.894	0.479	3.487	1	0.062	2.446
	N = 33,877; Nagelkerke R2 = 0.191						*N = 33,877; Nagelkerke R2 = 0.334*					

Source: authors' computations.