Research Policy 49 (2020) 104067

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Public R&D support and firm performance: A multivariate dose-response analysis

Øivind A. Nilsen[a,*], Arvid Raknerud[b], Diana-Cristina Iancu[c]

[a] Department of Economics, Norwegian School of Economics, Norway
[b] Research Department, Statistics Norway, Norway
[c] Division of Statistical Methods, Statistics Norway, Norway

ARTICLE INFO

Keywords:
R&D
Public policy instruments
Firm performance
Multivariate dose-response
Treatment effects
Matching
Output additionality

JEL classification:
C33
C52
D24
O38

ABSTRACT

We analyse all the major sources of direct and indirect research and development (R&D) support to the business enterprise sector in a single country, Norway, for the period 2002–2013, treating the financial support for R&D from several instruments as a multivariate dose exposure. The output additionality of support to incumbent firms that regularly perform R&D (*R&D-incumbents*), which obtain about 65 per cent of all R&D support to business enterprises, is insignificant for any instrument or policy mixture. However, the estimated additionality of support to *R&D-starters* (firms without prior R&D activity), which obtain about 30 per cent of all R&D support, is generally positive. In this firm category, the main instruments for direct R&D support in Norway generate significantly *less* output and economic activity per NOK 1 million in support than do tax credits, despite the fact these instruments manage large project portfolios at considerable administrative costs. We do not identify positive effects of R&D support on labour productivity or the return on assets for any of the instruments. Our main policy implication is that R&D instruments for the business enterprise sector should be designed in favour of R&D-starters over R&D-incumbents, that is, shifting the focus from the intensive to the extensive margin.

1. Introduction

There is a general understanding among economists that technological progress is closely linked to economic growth and that it is spurred by investment in research and development (R&D) (e.g., see Romer, 1990). Public support to private R&D is based on the notion that there are market failures and spillovers related to R&D (e.g., see Griliches, 1992). A common source of market failure is knowledge externalities. Such externalities may occur if it is difficult to establish ownership rights to new production methods or technologies, which enables competitors to take advantage of investment in R&D without bearing the costs.

The extent of public support to R&D has increased as a percentage of gross domestic product in most OECD countries over the last 10 years (see OECD, 2016, Fig. 4.7). However, the average gross domestic spending on R&D as a percentage of gross domestic product in these countries has been quite stable over 2000–2016, varying from 2.1 per cent to 2.4 per cent.[1] In this context, the goal of this paper is to evaluate quantitatively the economic benefits of R&D subsidies on firms' performance, given that in most countries there are several co-existing and potentially complementary R&D support schemes. We study a set of outcome variables related to output, employment, labour productivity (output per employee) and profitability. These outcome variables are highly relevant from a policy perspective as the subsidy instruments analysed are all intended to contribute to increased activity in R&D-intensive industries.

This article contributes to the literature on output additionality of R&D support to firms and to the small but growing literature on dose–response analysis.[2] Although there are other studies that address the issue of multiple sources of public R&D support (e.g., Czarnitzki and Lopes-Bento, 2013, and Dumont, 2017), to the best of our knowledge, there are no published articles that analyse *all* the major sources of R&D

* Corresponding author.
E-mail addresses: oivind.nilsen@nhh.no (&.A. Nilsen), arvid.raknerud@ssb.no (A. Raknerud), diana.c.iancu@gmail.com (D.-C. Iancu).

[1] Gross domestic spending on R&D is defined as the total expenditure (current and capital) on R&D carried out by all resident companies, research institutes, university and government laboratories, etc., in a country. See OECD (2018), gross domestic spending on R&D (indicator). doi: 10.1787/d8b068b4-en.

[2] Only R&D support to firms in the business enterprise sector is included in this study. Support to public and private (non-profit) R&D institutes and universities is out of our scope.

https://doi.org/10.1016/j.respol.2020.104067

Available online 28 July 2020

support in the business enterprise sector in a single country.[3] Our dose–response framework treats financial R&D support as a multivariate support-dose exposure, without making strong assumptions about the effects of policy instrument mixtures (For example, we do not assume that the instruments are perfect substitutes).

A major part of the existing literature on public R&D support analyses (R&D) input additionality. The literature focusing on output additionality or other outcome measures is much more limited.[4] Bronzini and Iachini (2014) and Bronzini and Piselli (2016) find positive effects on patenting of an R&D subsidy program in northern Italy, whereas Cappelen et al. (2012) find that the introduction of R&D tax credits in Norway contributed to an increase in (self-reported) new products and processes, but not to more patent applications. Dechezleprêtre et al. (2016) find that tax deductions for R&D expenses in the UK increased the propensity to patent. Turning to other outcome measures, Bodas-Freitas et al. (2017) find that R&D tax credit programs in Norway, France and Italy have led to an increase in firms' turnover from new products. Czarnitzki and Hussinger (2018) find that publicly induced R&D has a positive effect on the output growth of German firms. Hottenrott and Richstein (2020) also analyse German firms and find that grants and subsidized loans facilitate tangible investment, employment and revenue growth. Cin et al. (2017) find that a public R&D subsidy program in Korea increased private R&D investments and labour productivity for small and medium-sized firms (SMEs) in the manufacturing industry. Bérubé and Mohnen (2009) find that the revenue from new products is higher for subsidized than for non-subsidized Canadian firms. Using Canadian firm-level data, Czarnitzki et al. (2011) find positive effects of R&D tax credits on the number and sales of new products.

The main challenge in assessing the causal effects of R&D subsidy programs is endogenous selection into the programs based on unobserved or omitted variables that independently affect the outcome variable (*confounding factors*). Often, selectivity issues are not emphasized in the literature on the effects of R&D support programs (see Klette et al., 2000, and David et al., 2000). Our data have three unique features that we exploit to address such issues: (1) we have full coverage of limited liability firms receiving support over a relatively long time (2002–2013); (2) the data on public support are merged with other public registers that contain detailed information on accounting variables, employment and intellectual property rights (IP); and (3) the register data are merged with survey data on firms' R&D expenditures, which enables us to track the R&D history *prior to obtaining support* for more than 85 per cent of the firms that received any kind of public R&D subsidies during the observation period.

Using panel data, we observe the outcome variables over time before and after support and compare them with a control group of firms that did not receive any support, i.e., firms that are assumed to represent the non-treated (counterfactual) outcomes for those receiving support. A sufficiently large treatment group and a large reference population from which one can draw the control group are the necessary conditions to distinguish systematic differences from spurious correlations. Moreover, if the premises of the matching are met, the estimated effect can be interpreted as a causal effect of the policy instruments among the firms that received support.

Defining *R&D-experienced* and *R&D-starters* as, respectively, firms with and without R&D activity prior to receiving support, the findings indicate the following. First, the estimated dose–responses of R&D support tend to be positive and significant for R&D-starters, i.e. at the *extensive margin*, but they are clearly insignificant for R&D-experienced firms that were older than three years at the time of treatment assignment (henceforth referred to as *R&D-incumbents*). Second, our estimates are significant only for outcome variables related to growth in output and employment, but insignificant with respect to labour productivity and returns on assets. Third, we find that the effect of support is decreasing on the margin, as the level of support per firm-year (the *support dose*) increases. Fourth, despite managing large project portfolios with considerable administrative costs, the major instruments for direct support in Norway generate *less* additional output (value added) and employment per NOK 1 million in support than do tax credits. However, the comparatively positive effects regarding tax credits seem to be due to lower levels of support dose, rather than to specific characteristics of indirect vs. direct support.

The remainder of the paper is structured as follows: Section 2 presents information about the institutional setting in Norway. Section 3 presents the data. Section 4 describes the matching procedure and the general econometric model used for the analysis. Section 5 provides the main results and discusses policy implications. Finally, Section 6 concludes.

2. Institutional setting

Since 2002, the three main government instruments for promoting R &D and innovation in the business enterprise sector in Norway have been Innovation Norway (IN) and the Research Council of Norway (RCN), which provide direct support, and the R&D tax credit scheme *Skattefunn* (SKF), which provides indirect support. The goals and financial means of these three instruments differ somewhat.

IN's activities can be broadly divided into three main activities or programs: the innovation program, the district program and the lending program. Our study covers only the innovation program, as the other programs are not aimed at supporting R&D, but provide support to, for example, agriculture and sparsely populated regions. The goal of the innovation program is to promote profitable economic development by supporting innovative businesses.[5] The innovation program comprises instruments such as grants, innovation loans, high-risk loans and advisory services intended to promote new products, new technology, organizational innovations and growth. IN is required by the government to regularly provide impact assessments related to their activities, including estimates of output additionality. Small start-up firms and firms in specific technology areas (e.g., environmental technologies) are targeted through designated grants and specialized programs. The total support from IN's innovation program was NOK 1.1 billion in 2013. Furthermore, by allocating support through regional offices, in contrast to RCN and SKF, IN prioritizes an equal distribution of support across the main regions of Norway.[6]

The support provided by RCN, like that from IN, involves a selective instrument, with firms competing for funds.[7] Support to the business enterprise sector from RCN was NOK 1 billion in 2013. This represents only about 20 per cent of all R&D support from RCN, as the main beneficiaries are outside the business enterprise sector: Public and

[3] There are a few (unpublished) reports and working papers that analyse the same instruments as in our paper, including Bye et al. (2019), Cappelen et al. (2016) and Hægeland and Møen (2007).

[4] Some examples of the literature on *input* additionality are Wallsten (2000) (U.S. firms), Duguet (2004) (French firms), Czarnitzki and Licht (2006) (German firms), Lokshin and Mohnen (2013) (Dutch firms), Cappelen et al. (2010) and Bøler et al. (2015) (Norwegian firms) and Dumont (2017) (Belgian firms).

[5] IN explains its goal as follows: 'The main goal of Innovation Norway is to promote profitable business and economic development in general, and to promote the business opportunities in all regions through three subgoals: more high-quality entrepreneurs, more growing companies and more innovative business environments' (translation based on Innovation Norway, 2018, p. 8).

[6] See Cappelen et al. (2016), Table 3.5 and Fig. 3.3 (total amounts and regional distribution, respectively).

[7] The main argument for selective support schemes is that the government can channel support to projects that are expected to have major positive external effects and, consequently, projects for which the social returns are higher than private economic returns. For a theoretical basis for such project selection, see Jaffe (1998).

private (non-profit) research institutes received NOK 2.5 billion and the university and higher education sector received NOK 2 billion in 2013. RCN's support for the business enterprise sector does not specifically target basic scientific research, but is aimed broadly at commercial R&D that promote innovations and value creation for the supported firms.[8]

Through SKF, firms receive tax credits for R&D, comprising either tax deductions or cash refunds if a firm's tax credits exceed its taxes. SKF was introduced in 2002, originally to stimulate more SMEs to undertake R&D. Its scope was expanded in 2003, to include all firms in the business enterprise sector.[9] From 2003, the SKF scheme granted large firms (those with more than 100 employees) 18 per cent of R&D expenses related to an approved project, up to a limit of NOK 4 million. The rate for SMEs was 20 per cent of an approved project and, from 2009 to 2013, the maximum limit was NOK 5.5 million. Thus, the maximum tax relief for a large firm was about NOK 1 million (about EUR 110,000) in 2013.[10] The tax refund is granted at the end of the year in which the actual R&D expenses are incurred (assuming that the project was approved).[11] Total support from SKF was NOK 1.6 billion in 2013. In contrast to both IN and RCN, which select and actively manage a portfolio of research projects, SKF supports R&D *indiscriminately*, with minimal administrative costs. Each year about three-quarters of the total tax subsidies are given as cash refunds, suggesting that liquidity is the main motivation for applying for funds.[12]

An important difference between direct subsidies and tax credits is that the latter are obtained by many more firms than the former but in much smaller amounts per firm-year (one firm observed for one year). This is illustrated in Fig. 1, which shows the distribution of support for each scheme according to the amount of support per firm-year. For example, more than 60 per cent of the SKF subsidies amount to less than NOK 0.5 million per firm-year, compared with 35 per cent of IN and 30 per cent of RCN subsidies. On the other hand, a significant share of IN and RCN grants exceed NOK 6 million per year, and account for a large share of the *total* support to firms from IN and RCN.[13]

The same firm may obtain support from several instruments at the same time. In particular, an approved project from IN or RCN will normally provide a legal right to tax subsidies (but with an upper limit on total support owing to European Union rules for state subsidies). We define a *treatment* as a sequence of consecutive firm-years with support. This is independent of whether the support comes from one or multiple sources in (some or all) the years in the sequence. If a firm obtains repeated treatments, the new treatment period is, by definition, non-consecutive to the preceding one. The upper part of Table 1 shows that in the case of treatments with IN or RCN as the largest source of funding (columns 1–2), SKF is an additional source of funding in 45 per cent of the treatments (row 3). In contrast, in the case of treatments with SKF as the largest source of funding (column 3), additional support from IN and RCN is received in only 9 per cent and 5 per cent of the treatments, respectively (rows 1–2). The lower part of Table 1 shows that the largest source of R&D support accounts for 84–91 per cent of total treatment-level R&D support. When tax credits (from SKF) are the largest source of funding, direct grants account for an almost negligible share (0.03 + 0.04 = 0.07, i.e. 7 per cent) of total treatment-level support. If RCN or IN is the largest source of funding, tax credits contribute 13–14 per cent of total R&D support.

3. Operationalisations and data

Let D denote the number of years in the treatment (duration). To measure the treatment intensity, we define the support dose as the vector $S = (S_{(IN)}, S_{(RCN)}, S_{(SKF)})$, where the component $S_{(k)}$ is the sum of support from the instrument k over the whole treatment period *divided by D*.

The annual support data cover the period 2002–2013. These data are merged with annual register data covering accounting variables, employment and IP for all Norwegian limited liability firms since 1995. We will refer to these merged data as the Business Register. An additional source of information is the R&D census. This census is mandatory for all firms that are selected by Statistics Norway and it covers all firms in the business sector with at least 50 employees. It commenced in 1997 as a biannual survey and became annual in 2001. Among firms with 10–49 employees, a stratified random sample by two-digit NACE industry of about 30 per cent of the population is drawn each year from the main R&D industries (and smaller shares from the other industries). Firms with 5–9 employees are included in the census through a stratified random sample scheme, but with more limited coverage. Regardless of size or industry, all firms that reported significant R&D activity in the previous census are included in subsequent ones. To supplement the regular R&D census, we obtained questionnaire data from SKF on each applicant's R&D expenditure for three years prior to applying for tax credits. These data are collected by the RCN, which must approve in advance any project that is to form the basis for tax credits (see footnote 11).

Firms that obtain support but are missing from both the annual R&D census and the SKF questionnaire data are excluded from our estimation sample. Moreover, our model set-up requires matching of the treated firms with non-treated firms belonging to the same *stratum* at the time of matching, where the matching (stratification) variables include R&D expenditure, IP applications, employment, industry (two-digit NACE), region and firm age.

Our final matched sample is a combination of sampling from the R&D census and the Business Register, as firms that are R&D-experienced prior to obtaining support are matched with R&D active firms from the R&D census sample. On the other hand, R&D-starters, i.e. firms without R&D activity prior to treatment (according to both sources of R&D information), are matched with firms from the Business Register with no recorded R&D activity.[14]

[8] ‘ … (innovation support is aimed at projects with) … extensive content of research and development activities … (contributing to) … renewal and increased value creation for the firms that participate in the project, and for Norwegian firms in general by making new knowledge and new solutions available’ (translated from Research Council of Norway, 2019) (https://www.forskningsradet.no/sok-om-finansiering/hvem-kan-soke-om-finansiering/naringsliv/innovasjonsprosjekt-for-offentlig-og-naringsliv/).

[9] The EFTA Surveillance Authority (ESA) asserted that the original scheme violated EU rules against discriminatory government subsidies.

[10] Since then the limit has been increased several times. See Benedictow et al. (2018) for details about the scheme.

[11] Firms are entitled to tax credits as long as the project meets the formal criteria and has been approved by the Skattefunn division of the Research Council. This applies only to costs that the firms have incurred in the income year in which the approval was granted. The tax authorities monitor the reported costs and aggregate public support for the enterprise under the State Aid Code. See Benedictow et al. (2018) for further details.

[12] This share has remained remarkably stable over time (https://www.ssb.no/teknologi-og-innovasjon/artikler-og-publikasjoner/stor-okning-i-bruk-av-skattefunn-ordningen (in Norwegian)).

[13] Table A.1 in the Appendix provides further information about the distribution of support across industries and regions. Support is highly concentrated in a few industries, with two-thirds of total support going to manufacturing (with production of chemicals as the largest two-digit NACE industry), followed by information and communication (16 per cent) and professional and scientific services (12 per cent). An almost negligible share of the support goes to other industries. The distribution across regions and industries is similar across the support schemes except that a higher share of RCN support is received by professional and scientific services (which includes NACE 72) compared with support from IN and SKF.

[14] A firm in the Business Register with zero received R&D support and no recorded R&D activity (because it is missing from the R&D survey data) is classified as *R&D inactive*. According to our estimates, the probability that this is a misclassification is less than 3 per cent. The expected downward bias in the effect estimate (due to including potentially R&D active firms in the control group) is negligible.

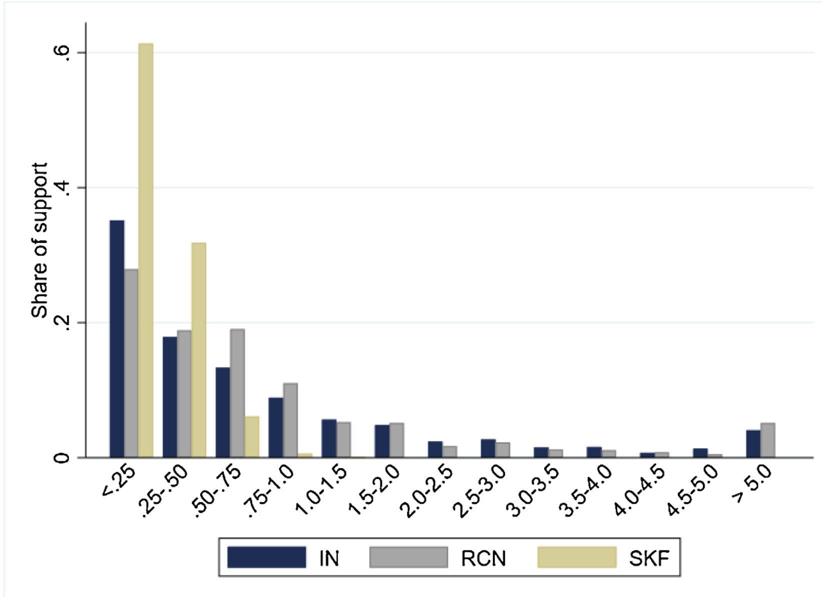

Fig. 1. Distribution of annual firm-level support for each policy instrument.
Notes: In millions of NOK (horizontal axis) per firm-year. The sum of the shares equals one for each instrument.

Table 1
Share of support from each policy instrument, by largest source of support.

	Largest source of support of the treatment		
Share of treatments supported by	IN	RCN	SKF
IN	1.00	0.18	0.09
RCN	0.07	1.00	0.05
SKF	0.45	0.45	1.00
Share of NOK million support from			
IN	0.84	0.04	0.04
RCN	0.03	0.82	0.03
SKF	0.13	0.14	0.93
Total	1.00	1.00	1.00

Notes: The upper part of the table reports the share of treatments that receive support from the given source (rows 1–3), for a given largest source of support of the treatment (columns 1–3). The lower part (rows 4–6) reports the share of support from each policy instrument.

3.1. Descriptive statistics before matching

The Business Register consists of 8834 treated firms and the total number of treatment years is 27,224, which comprises 4362 treatment years with support from IN, 3646 with support from RCN and 23,049 with support from SKF (note that the same firm may receive support from several sources in the same year). We observe that the total R&D support from the three instruments to the population of limited liability firms is NOK 21,924 million from 2002 to 2013. This sum is split between the three instruments as follows: NOK 5014 million from IN, NOK 6410 million from RCN and NOK 10,500 million from SKF. Column 2 contains descriptive statistics after the merger of the Business Register with our two sources of R&D survey data. Comparing columns 1 and 2 (the upper part of Table 2), it can be seen that having to classify firms as either R&D-starters or R&D-experienced at the time of treatment assignment reduces the number of treatment years by only 13 per cent (from 27,224 to 23,737) and the amount of R&D support from 21,924 to 19,100 million NOK.

From the three last columns in the upper part of Table 2, we can see that a highly disproportionate amount of R&D support is given to R&D-experienced firms (17,717 / 23,737).[15] From the lower part of Table 2, comparing columns 1–2 with columns 3–4, we see that the mean (median) number of employees among the treated firms is 32.1 (5.0) in the Business Registers compared with 39.7 (7.0) in the merged data set. The firms in the two data sets have almost identical characteristics for all other variables: the mean (median) level of labour productivity is 0.45 (0.40) vs. 0.46 (0.41), the mean (median) return on assets (RoA) is 1 (2) per cent vs. 2 (3) per cent and the mean (median) firm age is 8.6 (5.0) vs. 9.0 (5.0) years. Of the treated firms, 12 per cent have made a previous IP application, most commonly patents, before receiving support (first column). In contrast, only 0.8 per cent of all firms in the Business Register have IP applications (not displayed).

Some interesting differences with regard to the policy instruments appear in the upper part of Table 2. First, 31 per cent of all IN support goes to firms that are three years or younger (denoted by 'Share with firm age $\leq$ 3′), compared with 13 and 19 per cent for RCN and SKF (column 1). These figures confirm that IN specifically targets young firms. Perhaps surprisingly, a much higher share of support from SKF goes to firms that were R&D-experienced prior to treatment (78 per cent) compared with the proportions for IN (64 per cent) and RCN (59 per cent).[16] These figures reflect that tax credits are rights based. In contrast, RCN and IN choose projects based on internal evaluations of, among other things, prospective additionality. The result is a disproportional representation of (prior) R&D inactive firms compared with the 'pure' self-selection that characterizes SKF.

3.2. The matched sample

The purpose of matching is to control for confounding factors, i.e., variables that affect both the probability of treatment and the outcome variable, y. In our analyses, y equals either: (1) $\ln(Y)$ (log output), (2) $\ln(L)$ (log number of employees), (3) $\ln(Y/L)$ (log labour productivity) or (4) RoA (returns on assets). Our procedure is based on a vector of matching variables, X, which characterises the firm *prior* to receiving

[15] Only 4 per cent of all firms in the Business Register received any form of R&D support. Moreover, among firms that report positive R&D expenditure between 2002 and 2013 in the R&D census, 69 per cent received R&D support during the same period.

(footnote continued)

[16] From columns 2 and 4 (for IN, RCN and SKF): 2,636 / 4,116 = 0.64, 2,968 / 5,067 = 0.59 and 7,722 / 9,919 = 0.78.

Table 2
R&D support and pre-treatment characteristics (all treated firms).

	Business Register		Business Register merged with R&D data[1)]					
			All		R&D-starters[2)]		R&D-experienced[3)]	
No. of treated firms	8834		6838		2237		4601	
No. of treatment-years[4)]	27,224		23,737		6020		17,717	
# Firm-years with IN support	4362		3141		1261		1880	
-Share with firm age ≤ 3	0.38		0.37		0.64		0.20	
# Firm-years with RCN support	3646		3172		1063		2109	
- Share with firm age ≤ 3	0.17		0.17		0.33		0.09	
# Firm-years with SKF support	21,053		21,053		4802		16,251	
- Share with firm age ≤ 3	0.24		0.21		0.45		0.13	
Sum NOK million support 2002–2013	21,924		19,100		5776		13,300	
Sum IN support	5014		4116		1479		2636	
- Share with firm age ≤ 3	0.31		0.29		0.51		0.16	
Sum RCN support	6410		5067		2099		2968	
- Share with firm age ≤ 3	0.13		0.16		0.25		0.09	
Sum SKF support	10,500		9919		2196		7722	
- Share with firm age ≤3	0.19		0.18		0.41		0.03	
Pre-treatment firm characteristics	Mean	Median	Mean	Median	Mean	Median	Mean	Median
No. of employees[5)]	31.2	8.0	35.8	10.0	17.4	7.0	39.7	11.0
Labour productivity[5),6)]	0.45	0.43	0.46	0.43	0.37	0.33	0.49	0.47
RoA	0.01	0.02	0.02	0.03	−0.02	0.00	0.04	0.05
Firm age	8.6	5.0	9.0	5.0	7.5	2.0	10.6	7.0
R&D-intensity[7)]	NA	NA	0.06	0.02	0	0	0.09	0.03
Previous IP appl. (0/1)[8)]	0.12	0	0.13	0	0.0	0.0	0.17	0.00
- Patent appl. (0/1)	0.11	0	0.11	0	0.0	0.0	0.15	0.00
- Industrial design (0/1)	0.03	0	0.04	0.03	0.0	0.0	0.06	0.00

Notes: The table reports key variables at firm-year level for all treated firms in the Business Register compared with firms in the Business Register with R&D data (at the time of treatment assignment). The lower part of the table provides the mean and median values of key variables at firm-year level for 2002–2013. [1)] The data are from two sources: the annual R&D census and questionnaires to firms with support from SKF. [2)] R&D-starters: firms without R&D activity before obtaining support. [3)] R&D-experienced: firms with R&D activity before obtaining support.[4)] Some firms might receive support from several sources. Thus, the total for the rows might be larger than the number of treatment years. [5)] Firms with non-zero employment [6)] Output (value added) per employee in millions of NOK (NOK 100 ≈ EUR 11). [7)] Average NOK millions intramural R&D expenditures per employee over three years prior to treatment. [8)] Indicator of at least one IP application.

treatment. We divide X into a finite number of strata, x, as follows:

$$x = (industry, region, age, empl, rd, ip)$$

where *industry* is the two-digit NACE industry, *region* refers to one of five regions, *age* and *empl* refer to age and employment intervals, and *rd* and *ip* are dummy variables: $rd = 1$ if the firm was *R&D active* during the previous three years, and $ip = 1$ if the firm filed at least one application for IP during this period. The firm age intervals are 0–3, 4–6, 7–9 and >9 years, and the employment intervals are: 0–4, 5–9, 10–19, 20–49, 50–99, 100–249 and >249 employees. IP comprises patents and (industrial) designs registered at the Norwegian Patent Office.

In our study a firm is classified as R&D active if it reports positive R &D expenditures or file one or more IP applications. Thus, firms with $ip = 1$ is a subset of firms with $rd = 1$.[17] Therefore, our matching variables comprise indicators of the firm's prior R&D and innovation activities, which clearly affect both firm performance and participation in support programs. For example, without controlling for *prior* R&D activity, we risk confounding the effect of conducting R&D (and, perhaps, as a by-product, obtaining R&D support) with the effect of R&D support itself. Note that we do not use pre-treatment R&D-intensity as a continuous matching variable. This is partly because R&D-intensity, *conditional* on $rd = 1$, varies a lot over time for a given firm – and much more so than for the registry based variables. We suspect that measurement errors may partly contribute to this excess variation. The matching variables also reflect the fact that some programs target regions, start-up firms and industries, which is related to firm performance through local labour market and life-cycle conditions.

The upper panel of Table 3 shows that the final matched sample consists of 14,007 (3455 + 10,552) treatment years, comprising NOK 11,715 (3570 + 8145) million in total R&D support, of which about 70 per cent (8145 / 11,715) is allocated to firms that were R&D active at the time of treatment assignment (R&D-experienced). Comparing the characteristics of the treated firms (R&D-starters vs. R&D-experienced) in Tables 2 and 3 indicates that the (matched) estimation sample (the lower part of Table 3) is representative of the population of treated firms (the lower part of Table 2) along all dimensions of interest. This is further illustrated in Fig. A.1 in the Appendix, which shows the distribution of the number of employees at the year of treatment assignment before vs. after matching (treated firms with R&D information vs. treated firms in the matched sample). Although there is a slight tendency that the matched R&D-starters/-experienced comprise a slightly lower/higher share of firms with 1–5 employees compared to all treated firms, the overall picture is that the matched sample is a representative subset of all treated firms.[18]

[17] Note that if a firm receives R&D support (in t), then R&D expenditure (in t) is positive by definition, although it remains possible that the firm is R&D inactive: $rd = 0$ (recall that rd, like all other components of x, refers to the characteristics of the firm prior to treatment assignment). If so, treatment coincides with a transition from being R&D inactive to R&D active.

[18] The representativeness of the matched sample with respect to industry and region is generally good as shown by comparing Table A.1 (before matching) with Table A.2 (after matching). One exception concerns firms in the R&D industry (NACE 72), some of which receive large grants from RCN and co-operate closely with regional universities. Many treated firms in NACE 72 are not matched because there are few non-treated firms in this industry, particularly large ones. This is reflected in the lower shares of support after matching (Table A.2) than before matching (Table A.1) for the (broad) industry category professional, scientific and technical services, in which NACE 72 is included, and for the *Mid* region (where the Norwegian University of Science and Technology is located).

Table 3
Sample description and balancing properties (the matched sample).

	R&D-starters[1)]				R&D-experienced[2)]			
Sample size and support	Treated		Control		Treated		Control	
No. of firms	1135		68,930		3345		2954	
No. of treatment years	3455				10,552			
# treatment years with IN support	501				1174			
# treatment years with RCN support	732				1356			
# treatment years with SKF support	2771				9560			
Sum NOK million support [3)]	3570				8145			
Sum IN support	734				1717			
Sum RCN support	1580				1894			
Sum SKF support	1257				4533			
Balancing properties [4)]	Mean [5)]	SE	Mean	SE	Mean	SE	Mean	SE
Variables in levels (X):								
No. of employees	22.5	3.0	19.5	2.5	32.0	5.8	30.3	5.3
Labour productivity[6)]	0.48	0.03	0.44	0.02	0.49	0.03	0.50	0.02
RoA	0.052	0.007	0.052	0.007	0.051	0.017	0.050	0.006
Firm age	9.7	0.7	9.4	0.8	12.0	0.5	9.2	0.4
R&D-intensity[7)]	0	0	0	0	0.078	0.008	0.058	0.028
Prev. IP appl. (0/1) [8)]	0	0	0	0	0.064	0.005	0.063	0.006
No. of prev. IP appl.	0	0	0	0	0.193	0.030	0.201	0.030
Variables in differences (Δy):								
ΔLog no. of employees	0.04	0.01	0.05	0.01	0.04	0.01	0.06	0.01
ΔLog output	0.07	0.01	0.07	0.01	0.08	0.02	0.11	0.02
ΔLog labour productivity	0.03	0.01	0.04	0.01	0.06	0.02	0.04	0.01
ΔRoA	0.000	0.006	−0.001	0.005	0.019	0.010	0.010	0.006

Notes: [1)] R&D-starters: firms without R&D activity before obtaining support. [2)] R&D-experienced: firms with R&D activity before obtaining support. [3)] NOK million support 2002–2013. [4)] The matching is *exact* with respect to industry (two-digit NACE), region, IP applications (dummy) and the interval-valued firm age and employment variables used in the definition of the *strata* (see Section 3). [5)] Frequency-weighted means, with weights equal to number of treated firms in each *stratum.* [6)] Output (value added) per employee in millions of NOK (NOK 100 ≈ EUR 11). [7)] Average NOK millions intramural R&D expenditures per employee over three years prior to matching [8)] Dummy variable (indicator of at least one IP application).

The reduction in the sample size in Table 3 compared with all treated firms in Table 2 (i.e., 14,007 vs. 23,737) is the price that we pay for a matched sample with almost perfect balancing properties with regard to variables in levels (y, X) and in differences (Δy). From the lower part of Table 3, we can see that the balancing properties hold for the variables used in the matching, but also for labour productivity, R&D-intensity and RoA.[19] Perfect balancing regarding dummy or interval variables related to IP, R&D, firm age and employment is a direct result of the stratification. On the other hand, the almost perfect balancing with regard to the *level* variables in Table 3, such as number of previous IP applications, R&D-intensity, labour productivity, RoA and firm age, reflects the fact that none of these (level) variables are significant predictors of treatment assignment, conditional on the stratification (matching). The matching variables, conversely, are highly significant predictors of treatment assignment.[20] Moreover, the assumption of a common trend cannot be rejected for the pre-treatment differences (Δy) for any of the dependent variables, as seen from the lower part of Table 3.

4. Identification and estimation of treatment effects

In the classical case, treatment is represented by a binary treatment indicator, say D. In our set-up, a treatment is represented by a vector (D_i, S_i), where D_i denotes the number of years in the treatment period (duration), the subscript i denotes the firm and $S_i = (S_{i(IN)}, S_{i(RCN)}, S_{i(SKF)})$, where $S_{i(k)}$ denotes the support dose of firm i from the policy instrument $k \in \{IN, RCN, SKF\}$. As in the classical case, $D_i = 0$ is equivalent to non-treatment.

Let $y_{it}(d)$ denote the outcome when the firm is assigned to the treatment (or non-treatment) $d \in \{0, 1, 2, ...\}$ by a completely *random draw*. In contrast, $y_{it}(D_i)$ is the *realized* outcome, i.e., the outcome when D_i is selected by the process of application and approval described in Section 2. The amount of the support dose, S_i, is implicitly understood as a part of the treatment. Furthermore, let T_i denote the (firm-specific) year of treatment assignment (the firm receives support in T_i, but not in $T_i - 1$).[21] We assume, for $T_i \le t \le T_i + d$, that:

$$y_{it}(d) = f_i + m_t\left(X_{iT_i}\right) + \sum_{n=1}^{d} \tau_{in} 1_{(n \le t - T_i)} + e_{it}(d), \tag{1}$$

where f_i is a fixed firm effect, $m_t(\cdot)$ is the generic notation for the (non-parametric) *common trend,* X_{iT_i} refers to the characteristics of the firm *prior* to T_i, τ_{in} is a fixed treatment effect that is realized in year $t = T_i + n$. Moreover, $n \le d$, and $1_{(\cdot)}$ is notation for the dummy variable. Then, the effect of the treatment measured one year after end of treatment (at $t = T_i + d$) *or earlier* is:

$$E\left(y_{it}(d) - y_{it}(0)\right) = \sum_{n=1}^{d} \tau_{in} 1_{(n \le t - T_i)} \text{ for } T_i \le t \le T_i + d \tag{2}$$

Later, we consider the effects, τ_{in}, realized during the *post-treatment years*, defined as the years from $T_i + d + 1$ until the firm obtains a new treatment or exits from the sample. If present, such effects could be

[19] When the reported mean values are used with the standard errors to calculate 95 per cent (pairwise) confidence intervals for the treated and control groups and separately for R&D inactive and R&D active firms and for all the variables reported in the table, it can easily be seen that they overlap. Formal tests of equality of *means* and *medians* are available from the authors upon request. In all cases, these tests lead to clear non-rejection. We conclude that the matched sample has excellent balancing properties.

[20] Logit estimates, available from the authors upon request, support these statements.

[21] If a firm obtains repeated treatments, the estimation of treatment effects is based on a new matching for each treatment. Note that, by definition, a new treatment period is non-consecutive to the preceding period.

positive or negative. Positive effects would mean further additionality after the support has ended. Negative effects would mean reversion to the mean, i.e. that the potential positive effects of treatment start to diminish after the financial stimuli has ceased.

The main objectives of the estimation are *dose–response functions*, which are averages of the realized values of τ_{in} (i.e. for $n \leq D_i$) conditional on support dose, $S_i = S$, and pre-treatment characteristics $[X_{iT_i}]_{strat} = x$ ($[X]_{strat}$ denotes the stratification operator that maps X into x, see Section 3.2). Formally, a dose–response function is a conditional expectation:

$$\tau^{(x)}(S) = E\left(\sum_{n=1}^{D_i} \tau_{in}/D_i | S, x\right) \tag{3}$$

Duration, D_i, is allowed to depend both on effect parameters $\tau_{i1}, \ldots, \tau_{iD_i}$, support dose, S, and pre-treatment characteristics, x. For instance, treatments supported (mainly) by RCN tend to have longer durations than treatments supported (mainly) by SKF or IN (see lower part of Table 4).

The main condition for identification is that the matching vector consists of a sufficient number of variables to satisfy *unconfoundedness* (Rubin, 1990). Define $W_i = (D_i, S_i)$. Then:

$$W_i \perp y_{it}(d) | \left(X_{iT_i}, f_i\right) \text{ for any } d \in \{0, 1, 2, \ldots\} \text{ and } t \geq T_i.$$

Unconfoundedness implies that the non-treated outcome, $y_{it}(0)$, is conditionally independent of the realized treatment, W_i, given the matching vector, X_{iT_i}, and the fixed effect, f_i. The inclusion of fixed effects adds substantial flexibility as we do not need to consider the impact of time-invariant variables that are picked up by the fixed effect (see Arkhangelski and Imbens, 2019, for a similar approach). For example, we might expect *unobserved* traits, such as management quality, employer skills and capabilities to affect both firm performance *and* the probability of treatment (see Yu et al., 2015 and Sadun et al., 2017). To the extent that such traits are persistent, for example in the form of a high productivity *level*, they will be picked up by the fixed effect. Of course, such traits could also lead to higher than average productivity *growth*. However, as shown in the lowest part of Table 3, there is no systematic pre-treatment difference between the treatment groups and the control groups with respect to any of the growth variables that we consider, including labour productivity growth.

It would *not* be a violation of unconfoundedness if a firm has a research idea and then obtains R&D support. In fact, this is exactly what we expect to happen: projects are always approved based on ex ante plans and ideas. However, it would be a violation if innovative projects are carried out regardless of support *and* the firms in the control group are systematically less innovative. Fortunately, innovativeness is not completely unobserved, as firms tend to protect valuable innovations by applying for IP (patents, industrial designs, etc.). This is the reason that we have included a number of pre-treatment IP applications as a

Table 4
Estimated partial outcome additionalities.

Outcome variable	R&D- status	Age category	Policy instrument					
			IN		RCN		SKF	
			Addit.	z	Addit.	z	Addit.	z
Output (value added) (Y)	Starters[1)]	Start-ups[3)]	1.32*	1.90	0.73	0.45	3.16***	2.74
		Incumbents[4)]	1.34*	1.92	1.58	0.19	3.47***	2.50
	Experienced[2)]	Start-ups	0.52*	1.75	−0.23	−0.33	0.65**	2.05
		Incumbents	–1.02	–1.55	7.85	1.13	0.56	0.88
No. of employees (L)	Starters	Start-ups	0.68*	1.80	0.96	1.26	2.32***	2.66
		Incumbents	1.25*	1.69	10.44	1.14	5.38***	4.23
	Experienced	Start-ups	0.28	0.87	0.09	0.20	0.66**	2.08
		Incumbents	0.16	0.32	0.20	0.08	1.17	1.56
Labour productivity (Y/L)	Starters	Start-ups	0.09	0.16	–0.96	–1.00	0.55	0.68
		Incumbents	0.44	0.69	1.48	0.26	–0.73	–0.54
	Experienced	Start-ups	–0.16	–0.51	0.29	0.58	–0.01	–0.04
		Incumbents	–1.31	–2.01	10.03	1.27	–0.43	–0.70
Return on assets (RoA)	Starters	Start-ups	–0.02	–0.01	–3.42**	–2.04	–0.12	–0.25
		Incumbents	1.79**	2.35	–3.75	–0.66	–1.77	–1.23
	Experienced	Start-ups	0.10	0.47	0.40	0.53	–0.22	–0.43
		Incumbents	–13.73	–1.09	–0.25	–0.03	–1.85**	–2.14
Mean support dose (interquartile range in parentheses) [5)]	Starters	Start-ups	1.8	(0.3, 2.6)	2.3	(0.6, 3.3)	0.5	(0.2. 1.0)
		Incumbents	1.1	(0.2, 1.5)	1.0	(0.3, 1.5)	0.4	(0.1, 0.6)
	Experienced	Start-ups	1.8	(0.4, 1.9)	2.5	(1.1, 3.1)	0.6	(0.2, 0.8)
		Incumbents	1.7	(0.6, 2.0)	1.5	(0.5, 1.8)	0.5	(0.2, 0.7)
Share of support to	Starters	Start-ups	0.30		0.28		0.17	
		Incumbents	0.06		0.13		0.05	
	Experienced	Start-ups	0.26		0.22		0.23	
		Incumbents	0.38		0.37		0.55	
		Sum	1.00		1.00		1.00	
Mean (median) duration[6)]	Starters	Start-ups	2.3	(1)	4.9	(4)	3.0	(2)
		Incumbents	1.6	(1)	2.6	(2)	2.4	(2)
	Experienced	Start-ups	3.3	(3)	5.2	(4)	3.2	(2)
		Incumbents	2.2	(1)	4.1	(3)	2.8	(2)

Notes: The table reports the estimated average partial outcome additionalities (Addit.) (for output, number of employees, labour productivity and *RoA*), by policy instrument, R&D-status prior to support, and age category in the year of treatment assignment. The given policy instrument is considered the marginal source of funding. For outcomes Y and L, Addit. represents, respectively, additional NOK mill. output/no. of employees per NOK 1 mill. of support. For outcomes Y/L and RoA, Addit. represents, respectively, increase in labour productivity/return on assets per NOK 1 mill. in support per employee/per NOK mill. asset. The symbols ***, ** and * denote significant estimates at the 1, 5 and 10 per cent levels. [1)] R&D-starters: firms without R&D activity before obtaining support. [2)] R&D-experienced: firms with R&D activity before obtaining support.[3)] Firm age ≤ 3 at the *start* of the treatment period (therefore the share of support to start-up firms is higher than the share of support to the category "Share with firm age ≤3" in Table 2). [4)] Firm age >3 at the *start* of the treatment period. [5)] Mean *support dose* (i.e. sum of NOK million support from the given instrument divided by no. of years in the treatment period), with interquartile range in parentheses (conditional on dose > 0) [6)] Mean (median) duration of the treatment (no. of years) when the given instrument is *the largest source of support* of the treatment.

matching variable.

4.1. Estimation

We define the *cell* $C(x, T)$ as the set of firms in the stratum x at time T. The subset of firms in this cell that are assigned to treatment at T (i.e., firms with $T_i = T$) is denoted by $N^T(x)$. The corresponding control group, $M^T(x)$, is a subset of non-treated firms in $C(x, T)$.[22] All firms in cell $C(x, T)$ that are assigned to treatment at T will have the same control group (many-to-many matching) regardless of the realized treatment.[23]

To estimate $\tau^{(x)}(S)$, we apply a regression formulation of the matched difference-in-difference (DiD) estimator (see Lechner, 2010).[24] First, we insert the expression for $\tau^{(x)}(S)$ into Eq. (1). Second, we difference to eliminate the fixed effect and obtain:

$$\Delta y_{it}(D_i) = \Delta m_t(x, T) + I_{(t-T\leq D_i)} \sum_x \tau^{(x)}(S) 1_{([X_{iT}]_{strat}=x)} + \Delta\eta_{it}(D_i)$$
$$\text{for } i \in N^T(x),\ T < t \leq T + D_i$$

with

$$\Delta\eta_{it}(D_i) = I_{(t-T\leq D_i)}\left(\tau_{i,t-T} - \sum_x \tau^{(x)}(S) 1_{([X_{iT}]_{strat}=x)}\right) + \Delta e_{it}(D_i)$$

and

$$\Delta y_{jt}(0) = \Delta m_t(x, T) + \Delta e_{jt}(0) \text{ for } j \in M^T(x) \quad \text{and } t > T$$

The equation is estimated on the sample consisting of all matched firms (treated and controls) across the cells $C(x, T)$.

The notation $m_t(x, T)$ underscores that the common trend is specific for the cell $C(x, T)$, i.e. $\Delta m_t(x, T)$ is non-parametrically identified as a cell-specific time effect. It is important that $\Delta m_t(x, T)$ does not depend on variables that may be affected by the treatment, such as contemporaneous R&D or employment. Current endogenous variables are 'bad controls'. Therefore, our control variables are used for stratification (matching) only. Moreover, to identify the effect of the *same* treatment over time, the matching must be kept the same; otherwise, the estimated common trend would depend on the outcome of the treatment.

Our approach is in line with Lechner (2010) and Lechner and Wunsch (2013), who stress the importance of the balancing properties of the matched sample. Like us, they do not include control variables in the DiD part of the estimation, using them only for matching purposes. If the matched sample is balanced, there is no need for additional control variables.[25]

In contrast to the completely flexible, non-parametric common trend, in the interest of parsimony, the dose-response function $\tau^{(x)}(S)$ is allowed to depend on just two components of x (implicitly aggregating over the other components): (1) start-up firms, defined as firms that are less than three years of age (counted from the date of incorporation) at the start of the treatment vs. incumbent firms and (2) firms that have reported positive ex ante R&D activity before treatment (R&D-experienced) vs. firms that with no such activity (R&D-starters).

4.2. Dose–response analysis

From a program evaluation perspective, the amount of support provided by a public agency is highly relevant (see Baum and Cerulli, 2016). Therefore, we explore a dose–response association between a (continuous) public support exposure and the associated outcome, as explained above. We allow the effects to be non-linear and incorporate a full set of interactions between the three policy instruments. We follow Baum and Cerulli (2016) and Hottenrott and Lawson (2017) and specify the dose–response function defined in Eq. (3) as a polynomial. Our most general specification is a polynomial of the third order, but with interaction terms restricted to be of the second order:

$$\tau^{(x)}(S) = \sum_k \tau_k{}^{(x)} S_{(k)} + \sum_k \tau_{kk}{}^{(x)} S_{(k)}{}^2 + \sum \tau_{kkk}{}^{(x)} S_{(k)}{}^3 + \sum_{k>l} \tau_{kl}{}^{(x)} S_{(k)} S_{(l)} \tag{4}$$

where the summation is over $k \in \{IN, RCN, SKF\}$ and ($\tau_k{}^{(x)}$, $\tau_{kk}{}^{(x)}$, $\tau_{kl}{}^{(x)}$, $\tau_{kkk}{}^{(x)}$) are parameters to be estimated for a given x.[26]

Two special cases are of interest: (1) the instrument (k) has no effect on the outcome variable and (2) all the instruments are *perfect substitutes*, which means that the total sum of the support dose, $\sum_k S_{(k)}$, is what matters, not the instrument mixture. Both special cases amount to testable restrictions on the parameters.

When reporting results in Section 5, we will typically be interested in the level variables, e.g. output (Y), while the dependent variable is on logarithmic scale, $y = \ln(Y)$. Thus, the dose–response function in Eq. (4) must be transformed into a level effect, which we denote by $\tau_L{}^{(x)}(S)$. From Eq. (1):

$$Y_{it}(d) - Y_{it}(0) = Y_{it}(0)\left(\exp\left(\sum_{n=1}^{d} \tau_{in} 1_{(n\leq t-T_i)}\right) - 1\right) \simeq Y_{it}(0) \sum_{n=1}^{d} \tau_{in} 1_{(n\leq t-T_i)}$$

Thus

[22] In principle, any *non-treated* firm in $C(x, T)$ could be in the control group $M^T(x)$. Some additional details are in order here. First, a non-treated firm could potentially belong to several control groups (one for each T). We assign a firm to a (unique) control group according to a rule that attempts to balance the ratio of the number of treated firms to the number of control firms across cells. Second, we do not exclude firms from potentially being in a control group until they obtain treatment (if ever) because such exclusions would depend on future outcomes of endogenous variables (e.g., future R&D) and therefore violate the conditional independence assumption.

[23] The principle that the control group is independent of the realized treatment also applies to propensity score matching with multiple treatments. A common practice is to match a unit (i) that obtains a specific treatment (k) with a non-treated firm with the same probability of the chosen alternative, $\pi_k(x_i)$. Unfortunately, as shown by Lechner (2001), this strategy does not lead to a balanced distribution of x in the matched sample, even if the assumption of unconfoundedness holds. To be valid, the matching should be conducted with respect to the vector $\pi(x_i) = (\pi_1(x_i), ..., \pi_K(x_i))$ involving all the *potential* treatments to ensure it is independent of the realized treatment. A consequence is that propensity score matching may not be simpler than covariate matching with multiple treatments. In fact, it could be more complicated and more dependent on ad hoc functional form assumptions.

[24] There is an ongoing debate in the literature as to whether one would benefit from combining DiD and matching; see for instance Blundell and Costa Dias (2009), Imbens and Wooldridge (2009) and Lechner (2010) and (2015). We emphasize the argument of Blundell and Costa Dias that 'the combination of matching with DiD as proposed in Heckman et al. (1997) can accommodate unobserved determinants of the non-treated outcome affecting participation for as long as these are constant over time' (2009, p. 604).

[25] We estimate the regression equation using *xtmixed* in STATA on the matched sample of N treated firms and M controls, where the $\Delta m_t(\cdot)$ are specified as *random* cell-specific time effects. Weights and robust (clustered) standard errors are specified. The weights are $w_i = 1$ if $i \in N^T(x)$ and $w_i = M\#N^T(x)/(N\#M^T(x))$ if $i \in M^T(x)$ (#A denotes the number of elements in the set A). The random effect specification is justified if X_{iT} and D_i are independent in the *matched* sample. Unfortunately, even if stratification achieves independence of X_{iT} and D_i within each cell, this does not necessarily extend to the matched sample if the ratio of treated to controls varies across the cells. The weighting corrects this imbalance: $\sum_{j\in M^T(x)} w_j/\#N^T(x) = M/N$, i.e., the number of *weighted* controls per treated firm is M/N in each cell and, as a result, the total number of weighted controls is M (as in the unweighted sample).

[26] Because the dose–response function is linear in parameters, it is a straightforward matter to accommodate heterogeneous coefficients. Then, $\tau_k{}^{(x)}$ can be considered as a weighted average over treatment-specific parameters that capture both unobserved firm characteristics, e.g., the dose relative to the size of the underlying R&D project and the duration of the treatment.

$$\tau_L^{(x)}(S) \simeq E\left(Y_{i,T_i+D_i}(0)|x\right)\tau^{(x)}(S)$$

We apply the Duan smearing formula (Duan, 1983) to obtain a further improved approximation and the delta method to obtain standard errors.

A causal interpretation of the dose-response function requires that support dose, S_i, is exogenous given treatment (e.g., see Guardabascio and Ventura, 2014). In our application, this is likely. First, tax credits are approved independently of the outcomes – prospective or realized – of the supported projects. Second, grants from RCN or IN are based on evaluations (often external) that lead to a binary decision: approval or not. If approved, the size of the grant is under normal circumstances fixed throughout the project period and depend on the type of program (regional, industry-wide, entrepreneurial, etc.) and its budgetary constraints. According to our sources at RCN and IN, the size of a grant is rarely determined by ranking the *successful* applicants. Of course, this does not preclude the possibility that projects may be terminated owing to breach of contract, or that continued support may be contingent on certain outcomes.[27] This is not necessarily a problem in our model. For example, if a project supported by NOK 1 million per year in three years is extended by one year, the support dose (support per year of treatment) would still be NOK 1 million.

5. Estimation results

5.1. The dose–response function

In the first part of the results presentation, we will focus on the outcome variables of output and number of employees (we present results pertaining to labour productivity and RoA in the next subsection). From a policy perspective, the estimand of main interest is the effect of a given *amount* of support on the *level* of these variables, for example, what is the additional output (Y) or additional number of employees (L) generated per NOK 1 million of support?

We focus first on the effect of partially varying the dose of the *k'th* component of S, $S_{(k)}$. Let $\tau_L^{(x)}(S_{(k)},\ \cdot\ )$ denote $\tau_L^{(x)}(S)$ as a function $S_{(k)}$, for any fixed level of the other components (as indicated by '$\cdot$'). We furthermore define the *k'th* partial dose–response as:

$$\tau_L^{(x)}(S_{(k)},\cdot) - \tau_L^{(x)}(0,\cdot)$$

The *k'th* partial dose–response considers the *k'th* instrument as the marginal source of funding, with the level of support from the other sources taken as given. This may be a realistic description from the perspective of the public agencies. First, in most cases of funding by SKF, this agency is the only and obviously, therefore, the marginal source of funding (see Table 1). Second, in the case of co-funding from SKF, on the one hand, and IN *or* RCN on the other hand, the latter is the marginal source because the project would qualify for tax credits regardless of direct support. Third, as shown in Table 1, there are very few cases with support from all three sources.

Figs. 2 and 3 show estimates of *average* partial dose–responses for R&D-starters and R&D-experienced firms (prior to support), respectively. Each figure is obtained by setting, for $k \in \{IN, RCN, SKF\}$, the other components of S equal to their empirical values and then averaging over all treatments in the relevant subpopulation (indicated by x). Each figure contains two panels, with results for start-up firms ($\leq$ 3 years) in the upper panel and incumbent firms in the lower panel. Each of the 6 separate graphs in each panel corresponds to a combination of one of two outcome variables, output (column 1) or employment (column 2), and one of the three policy instruments (IN, RCN or SKF) (in row 1 – 3).

From Figs. 2 and 3, we first note that the distribution of dose differs dramatically between SKF, on the one hand, and IN and RCN on the other. In the figures, this is indicated by the three vertical (dashed) lines showing the interquartile range and the mean dose (the solid line) for each combination of main instrument and firm group. We see that the typical dose (annual support) for SKF lies between NOK 0.2 and 0.5 million (interquartile range), compared with NOK 0.5–2.0 million for both RCN and IN (recall that the support dose refers to support per *firm-year* of treatment). Furthermore, while the interquartile range for SKF is very similar for the three groups of firms, both RCN and IN seemingly prioritize young firms over incumbents, especially incumbent R&D-starters.[28] About 10 per cent of total grants and 5 per cent of total tax credits go to the latter group (see lower part of Table 4).

There are some notable results in Figs. 2 and 3. First, the dose–responses of R&D-starters are generally significant and positive, with the exception of RCN. Second, R&D support does not seem to generate positive additionality for R&D-experienced firms, except for support from SKF above the mean dose (about NOK 0.5 million). Third, the effect of support is decreasing on the margin, as the level of support per firm-year (dose) increases. Fourth, the 95 per cent confidence intervals (the vertical line segments) are rather wide. Nevertheless, the clear impression is that the additionality, i.e., the generated increase in the outcome variable, is rapidly decreasing on the margin as the dose increases. This seems to be the main reason why the results for SKF are generally more positive than those for IN and RCN.

Three tests regarding the dose–response functions in Eq. (4) are presented in Table A.3 for two outcome variables presented in Figs. 2 and 3. The first column in the table tests the hypothesis that *all* instruments have zero effect (H_0) for each category of firms. There are two unambiguous results. First, in the case of R&D-starters that are three years or younger at treatment assignment (start-ups), we clearly reject H_0 (p-value < 0.0001). Second, in the case of R&D-incumbents, we clearly do *not* reject H_0. In the second column of the table, we test whether the instruments are perfect substitutes within each firm category. The implication of this hypothesis is that, for a given x, only the amount of support matters, not the instrument *per se*. In general, the hypothesis is not rejected, implying that if we control for pre-treatment characteristics (x) *and* the amount of support (S), no instrument is better or worse than others in terms of dose–response. Of course, as we have seen in Table 2, the different instruments *do* select systematically different projects with regard to observed pre-treatment characteristics (x) and provide very different support doses (S). Therefore, non-rejection does not necessarily imply that all the instruments are 'equally good', only that there is no selection of projects based on *unobserved* characteristics that systematically produces different outcomes. Finally, the third column tests the hypothesis that there are no second- or third-order terms in the polynomial dose–response function. This hypothesis is clearly rejected in all cases where zero effects of all the instruments are also rejected. Thus, the dose–response polynomial cannot be reduced to a linear function.

5.2. Additionality

The ideal way to assess the effectiveness of the R&D support schemes might be through a cost–benefit analysis taking into account all direct effects, spillover effects, administrative costs and the opportunity costs of inputs used in production. However, to assess spillover effects requires a structural analysis, which is beyond the ambition of this paper. The indications from previous studies using Norwegian data

[27] In the cases of RCN and IN, most support is decided in advance and locked in in the form of two- or three-year contracts. Premature cancellations are unusual.

[28] It should not come as a surprise that the mean or median incumbent firm with no R&D history receives less annual support than do R&D inactive start-ups. In general, it is a well-established government policy that youth, *ceteris paribus*, is an advantage in the competition for research funds, especially in the absence of previous R&D-related output.

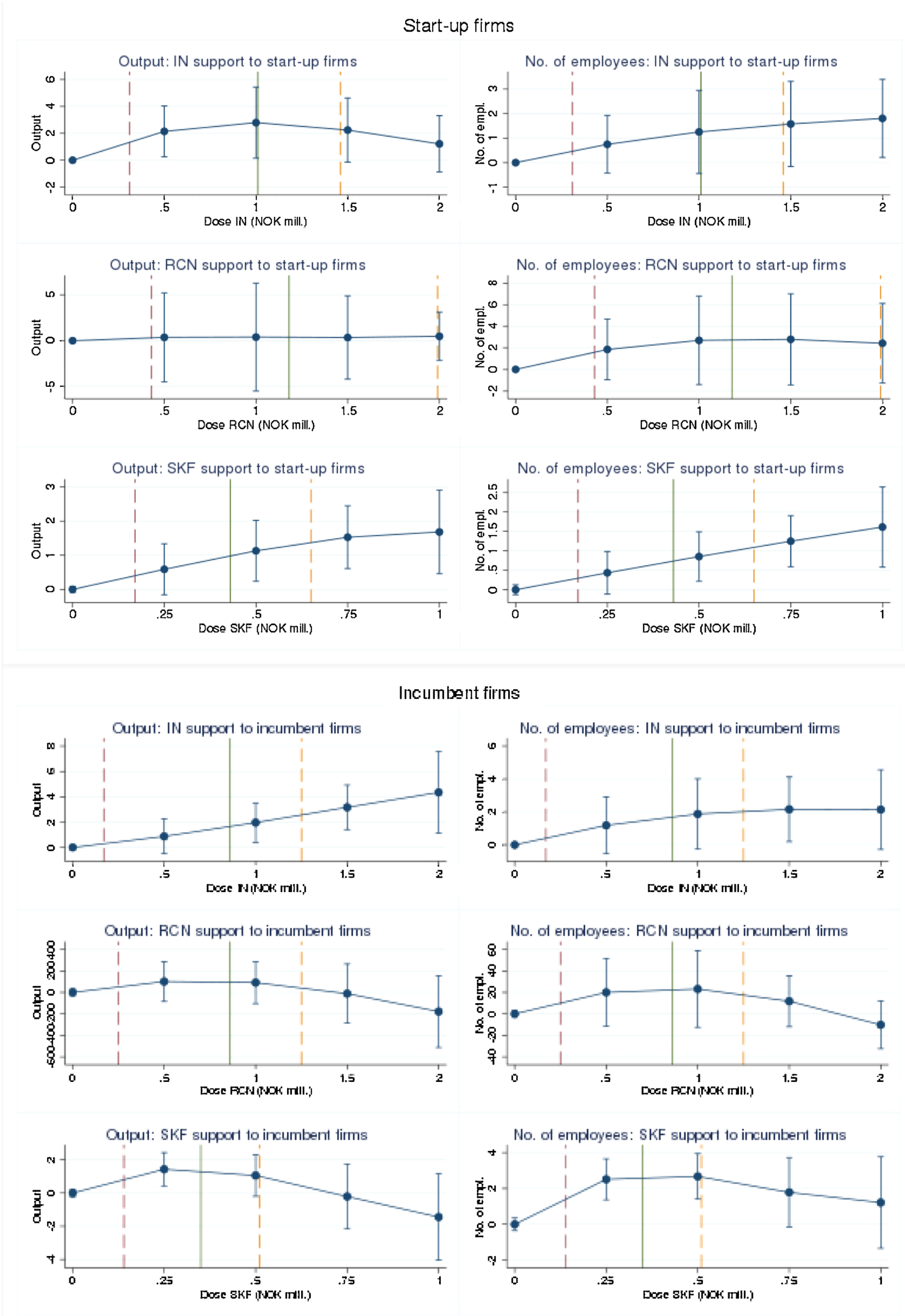

Fig. 2. R&D-starters: Estimated partial dose–response functions in levels.

Notes: The figures show the estimated partial dose–response functions in levels, by outcome (output, no. of employees), instrument (IN, RCN, SKF), and age category (start-ups, incumbents) for R&D-starters: R&D inactive firms prior to the support. Dose is defined as the sum of support from the given instrument divided by the duration of the treatment period. Vertical line segments indicate confidence intervals. The mean and the interquartile range of the support dose are indicated, respectively, by the solid vertical line and the pair of dashed vertical lines.

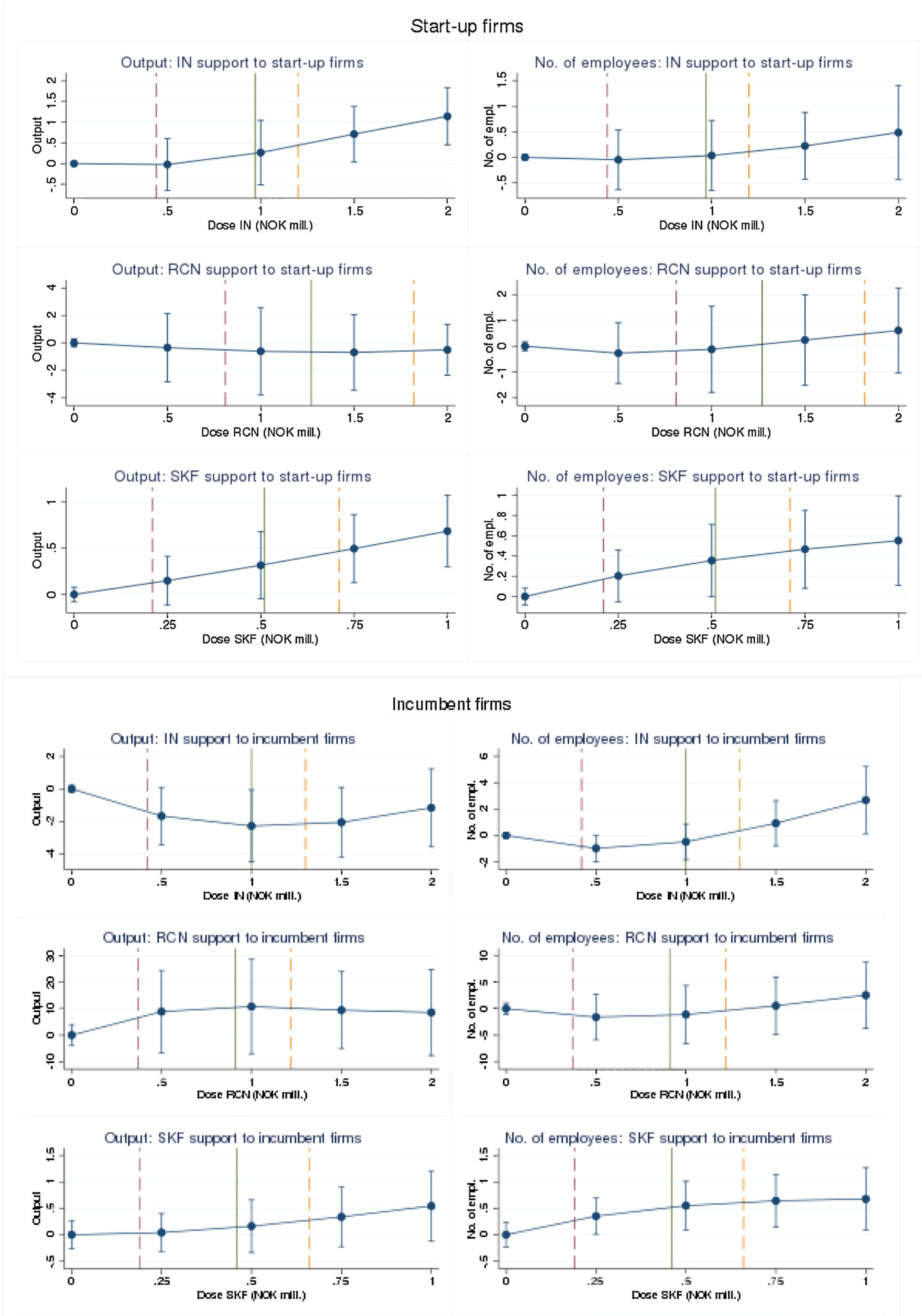

Fig. 3. R&D-experienced: Estimated partial dose–response functions in levels.

Notes: The figures show the estimated partial dose–response functions in levels, by outcome (output, no. of employees), instrument (IN, RCN, SKF) and age category (start-ups, incumbents) for R&D-experienced: R&D active firms prior to the support. Dose is defined as the sum of support from the given instrument divided by the duration of the treatment period. Vertical line segments indicate confidence intervals. The mean and the interquartile range of the support dose are indicated, respectively, by the solid vertical line and the pair of dashed vertical lines.

are that any spillovers are difficult to detect and, notwithstanding, difficult to attribute to specific policy instruments.[29] Our less ambitious approach, therefore, is to show that our dose–response framework is well suited to estimating familiar measures of additionality related to R&D support (see Mohnen (2018) for a discussion of different concepts of additionality).

We first consider output (value added) as the outcome variable. Dropping the subscript i, let $\Delta(Y) = Y_{T+D}(D) - Y_{T+D}(0)$ denote the additional output (the 'marginal effect') generated by total support $D \times \sum_k S_{(k)}$ (=duration $\times$ aggregate dose) over the treatment period. Then, *output additionality* can be expressed as:

$$E\left(\frac{\Delta(Y)}{D\sum_k S_{(k)}}\right) = E\left(\frac{\tau_L{}^{(x)}(S_{(k)},\cdot)}{\sum_k S_{(k)}}\right)$$

where the expectation is over the given subpopulation, defined in terms of x = (*industry, region, age, empl, rd, ip*). Output additionality is an expression for the average additional output per NOK 1 million of aggregate support. The right-hand side of the equation shows that output additionality can be calculated directly from the dose–response function.

We are more interested in the effect of a given instrument than in the aggregate support from all instruments. For this purpose, we define $\Delta_{(k)}(Y)$ as the additional output (marginal effect) of a partial increase in the support from the *k'th* instrument from zero to $S_{(k)} \times D$. Then, the additionality when the *k'th* policy instrument is considered the marginal source of funding can be expressed as:

$$E\left(\frac{\Delta_{(k)}(Y)}{DS_{(k)}}\right) = E\left(\frac{\tau_L{}^{(x)}(S_{(k)},\cdot) - \tau_L{}^{(x)}(0,\cdot)}{S_{(k)}}\right)$$

i.e., the numerator on the right-hand side equals the *k'th* partial dose–response and the denominator equals the corresponding dose.

The upper part of Table 4 shows the estimated partial additionalities corresponding to output (Y) and the number of employees (L). As explained above, these estimates are based on transformations of dose–response functions on a logarithmic scale (e.g., in the case of output, the dependent variable is $y = \ln(Y)$). Focusing first on R&D-starters, we see that the estimated additional output (the value added in NOK millions) per NOK 1 million in support from IN (SKF) is 1.32 (3.16) for start-up firms and 1.34 (3.47) for incumbent firms. The estimates of the additional number of employees per NOK 1 million in support from IN (SKF) are 0.68 (2.32) for start-up firms and 1.25 (5.38) for incumbent firms. The estimates for SKF are significant at the 1 per cent level, whereas the estimates for IN are significant only at the 10 per cent *or higher* level. Neither of the estimates related to support from RCN are significant. Turning to the results regarding R&D-experienced firms, we see that the estimated additionalities are either insignificant or much lower than for R&D-starters. Consistent with the tests reported in Table A.3, there are no significant estimates at the 10 per cent level for R&D-incumbents, whereas the highest significant estimate at the 10 per cent level is 0.66 for R&D-experienced start-ups.

The middle part of Table 4 shows estimates of additionality for labour productivity (Y/L) (obtained by transforming the dose–response function of $y = \ln(Y/L)$ and RoA). In these two cases, the outcome variable is a ratio, and we measure the support relative to the pre-treatment value of the *denominator* (L or K), rather than the (NOK million) support. What is shown in the table is the average increase in labour productivity per 1 NOK million in support *per employee* and the average increase in RoA per NOK 1 million in support *per asset* (book value, in NOK millions). Regarding labour productivity, none of these are estimates significant at the 10 per cent level, whereas the estimates for RoA are insignificant at the 10 per cent level, except for three cases, of which two are *negative*. These latter results show that support does not improve the productivity or profitability of the supported firms.

To summarize our results regarding additionality, public R&D support generates significant output and employment additionality among R&D-starters. These firms obtain 30 per cent of all R&D support to business enterprises.[30] On the other hand, there are no significant results for R&D-incumbents, which obtain 65 per cent of the support.[31] The results for the (residual) group of R&D-experienced start-ups are mixed, but this group obtains only 5 percent of total support. None of the instruments improve labour productivity or the RoA. The most striking finding is perhaps that—despite their active management of project portfolios at considerable administrative costs—neither IN nor the RCN generate more value added or employment relative to the amount of direct support than SKF does relative to the amount of tax credits. However, the generally higher and more significant additionality estimates for SKF compared with the other instruments do not necessarily mean that SKF is a 'better' instrument than IN or RCN. In fact, the higher additionality can be explained entirely by the decreasing returns to support dose, which was illustrated in Figs. 2 and 3 and corroborated by the test results in Table A.3. Moreover, the higher additionality of SKF compared with IN and RCN is restricted to R&D-starters, and the share of support to such firms is much lower for SKF (22 per cent) compared with IN (36 per cent) and RCN (41 per cent), as seen from the lower part of Table 4 (cf. also Table 2).[32] Because SKF is a rights-based instrument, in contrast to IN and RCN, it cannot target the category of firms that are mostly affected by R&D subsidies.

5.3. Post-treatment effects

So far, we have only considered the effects of the treatments that are realized within one year of the last year of support ($T_i + d$). If the duration of the treatment is long enough, this may be enough time for the effects to appear. However, given that a firm is not assigned to a new treatment, we may expect additional *post-treatment* effects in the forms of: (1) (positive) delayed effects and (2) (negative) mean reversion effects owing to the removal of the financial support. The net effect is indeterminate.

In contrast to the analyses above, we now consider the post-treatment years, i.e. the years from $T_i + d + 1$ until the firm obtains a new treatment or exits from the sample. Specifically, we will examine the 3-year post-treatment period from $T_i + d + 1$ until $T_i + d + 3$.[33] Extending Eq. (2), the effect of the treatment can be written as:

$$E(y_{it}(d) - y_{it}(0)) = \sum_{n=1}^{d} \tau_{in} 1_{(n \le t - T_i)} + \sum_{n=d+1}^{d+3} \tau_{in} 1_{(n \le t - T_i)}$$
$$\text{for } T_i \le t \le T_i + d + 3,$$

[29] Møen (2007) investigates spillovers that occur through labour mobility of R&D personnel, but finds no evidence that the personnel earn higher wages compared with a control group with similar experience, education, etc. Moreover, spin-off firms from the subsidized firms tend to perform *worse* than does a control group. However, in a related article, Møen (2005) finds moderate evidence of spillovers occurring through labour mobility between R&D-intensive firms. However, the latter article does not specifically address spillovers from publicly supported R&D.

[30] 5, 766/19, 100 = 0.30 (see columns 2-4 in Table 2).

[31] 0.70 × 0.93 = 0.65, where 0.70 is the estimated share of support to R&D experienced firms relative to all firms (13, 300/19, 100) (see columns 2-4 in Table 2) and 0.93 is the estimated share of support to R&D-incumbents relative to all R&D-experienced: 1 minus a weighted average of 0.16 for IN (about 25 per cent weight), 0.09 for RCN (about 25 per cent weight) and 0.03 for SKF (about 50 per cent weight); see column 4 in Table 2.

[32] From *Share of support* in Table 4, we have 0.30 + 0.06 = 0.36 (IN), 0.28 + 0.13 = 0.41 (RCN) and 0.17 + 0.05 = 0.22 (SKF).

[33] The choice of three years is motivated by Table A.4 which shows that 3 is the median number of post-treatment years in the sample. That is, at least 50 percent of all treatments can be followed for three post-treatment years. The longer the duration of the treatment, the fewer are the available post-treatment years that can be analysed.

Table 5
Estimated post-treatment partial outcome additionalities.

		Outcome variable					
		Output (Y)			No. of employees (L)		
R&D status	Policy instrument	Addit.	95% Conf.		Addit.	95% Conf.	
Starters[1)]	IN	−0.2	−4.3	4.1	0.5	−1.6	2.3
	RCN	−5.9	−28.1	17.1	5.8	−5.2	16.8
	SKF	3.0	−2.8	8.8	0.7	−3.1	4.4
Experienced[2]	IN	−0.5	−3.1	2.0	−0.1	−1.6	1.6
	RCN	3.3	−4.5	10.0	−2.8	−11.7	6.0
	SKF	0.3	−2.9	3.2	−0.6	−2.6	1.5

Notes: The table reports estimated post-treatment additionalities (Addit.) (for number of employees and output), by policy instrument and R&D-status prior to support. It reports the mean additional NOK mill. output (Y) and no. of employees (L) over the *three post-treatment years* per NOK 1 million of support. The given policy instrument is considered the marginal source of funding. The 95 per cent confidence intervals of Addit. is abbreviated *95% Conf.* The symbols ***, ** and * denote significance at the 1, 5 and 10 per cent levels. [1)] R&D-starters: firms without R&D activity before obtaining support. [2)] R&D-experienced: firms with R&D activity before obtaining support.

where the second sum refers to the 3-year post-treatment period. To obtain identification, we need to condition on no new treatment in the post-treatment period, as we cannot otherwise disentangle the effects of the new and previous treatments. A corresponding post-treatment dose–response function (cf. Eq. (2)) can be defined as:

$$\tau_{post}{}^{(x)}(S) = E\Big(\sum_{n=D_i+1}^{D_i+3} \tau_{in}/D_i|S, x\Big).$$

Table 5 presents estimates for the average post-treatment additionality. It is analogous to Table 4, but restricted to output and employment additionality. There are no significant estimates in Table 5, which indicate that the effects of R&D support are completely realized within one year of the end of the treatment. In addition, the results in Table 5 indicate that the gains achieved during the treatment period are not reversed over the next three years.[34] Thus, it is interesting to see that there are no additional effects after the treatment is finished, but neither are there any reversals. This result indicates that positive effects, if any, have a lasting impact on firm performance and that support does not merely give a transitory boost.

Table A.1
Percentage of R&D support, by broad industry and region. Before matching.

	Source of support			
Industry	IN	RCN	SKF	All
Primary industries	5.4	0.8	3.4	3.1
Mining, oil and gas extraction	0.4	2.2	0.9	1.2
Power prod., waste and recycling	1.0	1.7	1.3	1.3
Manufacturing	32.1	34.5	31.0	32.3
-Textiles and food	6.9	2.1	5.2	4.6
-Wood, pulp and paper	1.7	1.1	1.9	1.6
-Chemicals, pharma., rubber and plastics	4.1	4.6	3.3	3.9
-Metals and minerals	6.8	7.9	4.6	6.1
-Machinery and electronics	12.6	18.9	16.0	16.1
Construction	1.1	1.0	2.0	1.5
Wholesale and retail trade	5.5	1.9	8.1	5.7
Transportation and storage	1.2	1.6	1.1	1.3
Information and communication	20.8	12.6	27.0	21.4
Real estate activities	0.4	0.3	0.7	0.5
Professional, scientific and technical services	29.5	37.4	21.6	27.9
Other services	2.6	5.9	2.9	3.7
Sum of all industries	100	100	100	100
Region				
South	2.7	5.2	5.6	5.5
Capital (Oslo)/greater capital area	59.7	52.2	52.7	56.6
West	24.5	27.7	27.4	24.7
Mid	11.4	10.2	10.7	6.7
North	1.6	4.7	3.5	6.6
Sum	100	100	100	100

Table A.2
Percentage of R&D support and firm-years, by broad industry and region. After matching.

	Source of support				Firm-years
Industry	IN	RCN	SKF	All	
Primary industries	5.2	1.1	3.8	3.4	1.6
Mining, oil and gas extraction	0.8	1.8	1.0	1.1	0.5
Power prod., waste and recycling	1.0	2.0	1.6	1.6	0.9
Manufacturing	32.5	26.2	31.8	30.3	6.0
-Textiles and food	6.6	1.3	4.9	4.2	1.1
-Wood, pulp and paper	1.7	0.7	1.7	1.4	1.1
-Chemicals, pharma., rubber and plastics	4.1	5.7	4.1	4.6	0.4
-Metals and minerals	5.7	4.2	5.1	5.0	1.2
-Machinery and electronics	14.3	14.3	16.0	15.1	2.2
Construction	0.8	0.5	1.8	1.2	11.3
Wholesale and retail trade	5.3	2.3	7.5	5.5	19.0
Transportation and storage	1.4	0.9	1.1	1.1	4.1
Information and communication	16.7	8.2	25.2	18.3	4.1
Real estate activities	3.8	0.3	0.8	1.3	22.9
Professional, scientific and technical services	27.2	51.7	21.6	31.7	10.8
Other services	5.3	5.0	3.6	4.4	18.0
Sum industries	100	100	100	100	100
Region					
South	9	2	5	5	6
Capital/greater Oslo area	41	46	49	46	53
West	33	23	28	28	26
Mid	10	25	11	15	8
North	7	5	6	6	8
Sum regions	100	100	100	100	100

6. Concluding remarks

R&D investment is considered to be one of the main drivers of technological progress and economic growth. However, owing to market failures, there is ample support among policymakers and academics for increased public R&D expenditure. In many countries, including Norway, there are several co-existing and potentially complementary support schemes. We analyse all the major instruments for R&D support to firms in the business enterprise sector in Norway: the innovation-oriented policies of IN, the instruments of RCN and the R&D tax incentive scheme, SKF. Although the targeted firms and the design and magnitude of support are somewhat different, all three are intended to promote product or technology innovations. We consider R&D support as a multivariate dose exposure, allowing any mixture of support from the three instruments, and estimate dose–response functions on a sample of treated firms matched with a control group. Our data contain detailed accounting, employment and IP information from public registers, as well as information about R&D activity *prior* to obtaining support from two survey datasets. In particular, pre-treatment R&D is an important confounding factor. If we do not include this as a matching variable, our estimates of economic additionality become much higher.

The findings indicate the following. First, the estimated dose–responses are positive and (statistically) significant mostly in the case of

[34] As a supplementary analysis, we examined whether there are any differences in the post-treatment effects of treatments with durations exceeding three years vs. shorter durations. However, we found no interesting patterns or significant differences in the results between the two groups. These results are not shown, but are available from the authors on request.

Table A.3
Tests of parameter restrictions in dose–response function: *p*-values of χ^2- statistics.

Outcome variable	R&D-status	Age category	*p*-value of testing the hypothesis (H_0):		
			All instruments have zero effect[1)]	All instruments are perfect substitutes[2)]	No higher order terms in polynomial [3)]
Output (value added)	Starters[4)]	Start-ups[6)]	0.000	0.145	0.000
		Incumbents[7)]	0.103	0.252	0.432
	Experienced[5)]	Start-ups	0.035	0.827	0.000
		Incumbents	0.117	0.577	0.290
No. of employees	Starters	Start-ups	0.000	0.407	0.000
		Incumbents	0.000	0.878	0.000
	Experienced	Start-ups	0.000	0.000	0.000
		Incumbents	0.076	0.054	0.090

Notes: See Eq. (4). [1)] Test of ($\tau_k{}^{(x)}$, $\tau_{kk}{}^{(x)}$, $\tau_{kl}{}^{(x)}$, $\tau_{kkk}{}^{(x)}$) = 0 for all k, $k > l$ (11 degrees of freedom) [2)] Test of $\tau_k{}^{(x)} = \tau_l{}^{(x)}$, $\tau_{kk}{}^{(x)} = \tau_{ll}{}^{(x)}$, $\tau_{kkk}{}^{(x)} = \tau_{lll}{}^{(x)}$, $\tau_{kl}{}^{(x)} = 0$ for all $k > l$ (8 df.) [3)] Test of $\tau_{kk}{}^{(x)} = 0$, $\tau_{kkk}{}^{(x)} = 0$, $\tau_{kl}{}^{(x)} = 0$ for all $k \neq l$ (8 df.). [4)] R&D-starters: firms without R&D activity before obtaining support. [5)] R&D-experienced: firms with R&D activity before obtaining support. [6)] Firm age ≤ 3 at the *start* of the treatment period. [7)] Firm age >3 at the *start* of the treatment period.

Table A4
The number of post-treatment years.

Duration of treatment	Share with ≥ 3 post-treatment years	Median no. of post-treatment years	Cumulative share of all treatments
1	0.57	3	0.25
2	0.53	3	0.49
3	0.52	3	0.64
4	0.52	3	0.74
5	0.42	2	0.82
6	0.38	1	0.87
7	0.30	1	0.91
8	0.19	0	0.93
9	0.00	0	0.95
10	0.00	0	0.97
11	0.00	0	0.99
12	0.00	0	0.99
13	0.00	0	1.00

Notes: The post-treatment years start at the second, subsequent year after the end of treatment. For instance, if the treatment ends in 2009, the post-treatment years are the years from 2011 until the firm exits from the sample or obtains a new treatment.

R&D-starters (i.e. firms without R&D activity prior to receiving support), but insignificant in the case of R&D-incumbents (R&D active, incumbent firms prior to receiving support). Second, our estimates are significantly positive only for outcome variables related to output and employment, but insignificant with respect to labour productivity and RoA. Third, the dose–response is decreasing on the margin, causing a decreasing return to a higher support dose. Fourth, direct support from IN and RCN generate *less* additionality than does SKF per NOK million in support, despite active selection and management of projects, especially large ones, by IN and RCN. Given the mentioned result of decreasing returns to support, the comparatively positive effects regarding SKF seem to be due to their lower levels of support dose, rather than to specific characteristics of indirect vs. direct support. That is, notwithstanding active portfolio management, large projects do not appear to pay off.

Our analyses have strong policy implications: when economic additionality is of importance, policymakers should design R&D policy instruments in favour of R&D-starters, that is, shifting the focus from the intensive to the extensive margin. For other purposes, such as supporting regular R&D performers, it should be on the basis that the project will have positive spillovers, e.g. in the form of non-proprietary technology which may be beneficial to third parties.

There are issues not addressed that could to be explored in future work. First, we cannot observe whether the firms perform basic research or more development-type projects. Such heterogeneity may lead to different outcomes, and therefore, ideally, should be analysed separately. A second issue could be to look more into firms that can be followed over repeated treatments, or over longer post-treatment periods than we have done (i.e. three years). In any case, our multivariate dose-response framework can be applied, as it is quite flexible with regard to handling different sources and durations of support, as well as repeated support.

Declaration of Competing Interest

None

Acknowledgements

We especially thank three anonymous referees and an editor for numerous comments and suggestions, and Marina Rybalka for significant help in preparing and making available an R&D survey data set that has never previously been used in research. We are grateful for fruitful discussions with Philipp Boeing, Ådne Cappelen, Fulvio Castellacci, Erik Fjærli, Magnus Gulbrandsen, Hanna Hottenrott, Pål Aslak Hungnes, Øystein Jørgensen, Pierre Mohnen, Olav Naas and Terje Skjerpen, and for valuable comments during presentations at UNU-MERIT in Maastricht, at workshops arranged by the Oslo Institute for Research on the Impact of Science (OSIRIS) in Manchester and Oslo, the 8th InnoPat Conference ZEW/MaCCi Mannheim and the CATE Workshop at the Norwegian Business School. We acknowledge financial support from the Research Council of Norway through grant 256240 (OSIRIS)

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2020.104067.

APPENDIX

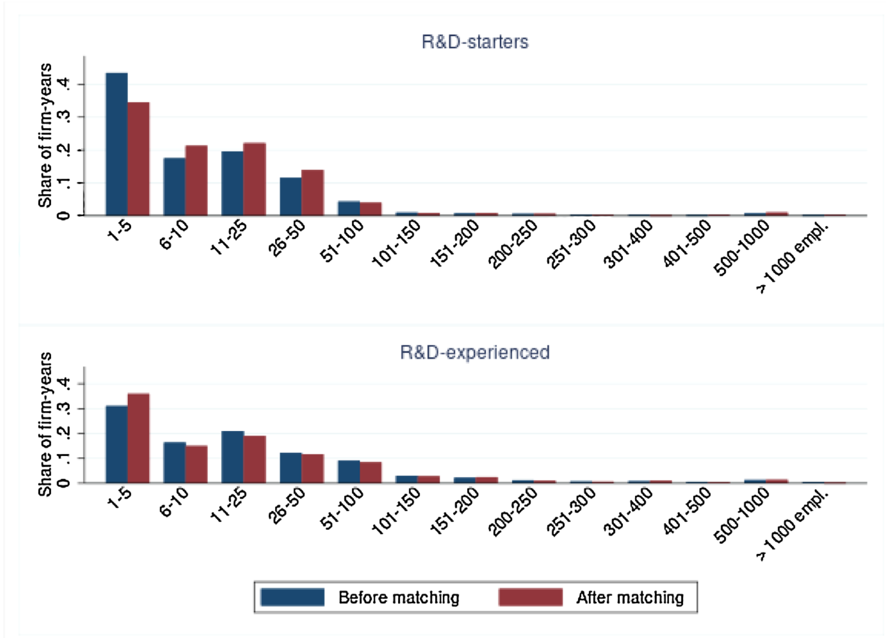

Fig. A.1. Distribution of number of employees at treatment assignment before and after matching, by R&D-status.
Notes: R&D-starters: firms without R&D activity before obtaining support. R&D-experienced: firms with R&D activity before obtaining support.

References

Arkhangelski, D., Imbens, G.W., 2019. The Role of the Propensity Score in Fixed Effect Models. Madrid, Spain CEMFI Working Paper No. 1905.

Baum, C.F., Cerulli, G., 2016. Estimating a Dose–Response Function With Heterogeneous Response to Confounders When Treatment is Continuous and Endogenous. Rome, Italy CNR-IRCrES, EcoMod 9388.

Benedictow, A., Bjoru, E.C., Eggen, F.W., Norberg-Schulz, M., Rybalka, M., Rotnes, R., 2018. Evaluation of SkatteFUNN. Samfunnsøkonomisk Analyse Technical Report 18.

Bérubé, C., Mohnen, P., 2009. Are firms that receive R&D subsidies more innovative? Can. J. Econ. 42 (1), 206–225.

Blundell, R., Costa Dias, M., 2009. "Alternative approaches to evaluation in empirical microeconomics. J. Hum. Resour. 44 (3), 726–759.

Bodas-Freitas, I.B., Castellacci, F., Fontana, R., Malerba, F., Vezzulli, A., 2017. Sectors and the additionality effects of R&D tax credits: A cross-country microeconometric analysis. Res. Policy 46 (1), 57–72.

Bye, B., Klemetsen, M., Raknerud, A., 2019. The Impact of Public R&D Support On firms' Patenting. Statistics Norway, Oslo, Norway Discussion Papers no. 911.

Bøler, E.A., Moxnes, A., Ulltveit-Moe, K.H., 2015. "R&D, international sourcing, and the joint impact on firm performance" Am. Econ. Rev. 105 (12), 3704–3739.

Bronzini, R., Iachini, E., 2014. Are incentives for R&D effective? Evidence from a regression discontinuity approach. Am. Econ. J. Econ. Policy 6 (4), 100–134.

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

Cappelen, Å., Fjærli, E., Foyn, F., Hægeland, T., Møen, J., Rybalka, M., Raknerud, A., 2010. Evaluation of the Norwegian R&D tax credit scheme. J. Technol. Manag. Innov. 5, 97–109.

Cappelen, Å., Raknerud, A., Rybalka, M., 2012. The effects of R&D tax credits on patenting and innovations. Res. Policy 4 (1), 334–345.

Cappelen, Å., Fjærli, E., Iancu, D.-.C., Klemetsen, M., Moxnes, A., Nilsen, Ø.A., Raknerud, A., Rybalka, M., 2016. *Innovasjons- og verdiskapingseffekter Av Utvalgte Næringspolitiske Virkemidler* (Innovation and Value Creation Effects of Some Governmental Financing Policies schemes), Reports 2016/12. Statistics Norway, Oslo, Norway.

Cin, B.C., Kim, Y.J., Vonortas, N.S., 2017. The impact of public R&D subsidy on small firm productivity: Evidence from Korean SMEs. Small Bus. Econ. 48, 345–360.

Czarnitzki, D., Licht, G., 2006. Additionality of public R&D grants in a transition economy: The case of Eastern Germany. Econ. Transit. 14 (1), 101–131.

Czarnitzki, D., Hanel, P., Rosa, J.M., 2011. Evaluating the impact of R&D tax credits on innovation: A microeconometric study on Canadian firms. Res. Policy 40, 217–229.

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

Czarnitzki, D., Hussinger, K., 2018. Input and output additionality of R&D subsidies. Appl. Econ. 50 (12), 1324–1341.

David, P.A., Hall, B., Toole, A.A., 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Res. Policy 29, 472–495.

Dechezleprêtre, A., Einiö, E., Martin, R., Nguyen, K.-.T., van Reenen, J., 2016. Do Tax Incentives For Research Increase Firm innovation? An RD design For R&D. Centre for Economic Performance, London School of Economics, London, UK CEP Discussion Paper No. 1413.

Duan, N., 1983. Smearing estimate: A nonparametric retransformation method. J. Am. Statist. Assoc. 78 (3838), 605–610.

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

Dumont, M., 2017. Assessing the policy mix of public support to business R&D. Res. Policy 46 (10), 1851–1862.

Griliches, Z., 1992. The search for R&D spillovers. Scand. J. Econ. 94 (0), S29–S47.

Guardabascio, B., Ventura, M., 2014. Estimating the dose–response function through a generalized linear model approach. Stata J. 14 (1), 141–158.

Heckman, J., Ichimura, H., Todd, P., 1997. "Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. Rev. Econ. Stud. 64 (4), 605–654.

Hottenrott, H., Lawson, C., 2017. Fishing for complementarities: Research grants and research productivity. Int. J. Ind Organ. 51, 1–38.

Hottenrott, H., Richstein, R., 2020. Start-up subsidies: Does the policy instrument matter? Res. Policy 49 (1) ??-??.

Hægeland, T., Møen, J., 2007. The Relationship Between the Norwegian R&D Tax Credit Scheme and Other Innovation Policy Instruments. Statistics Norway, Oslo, Norway Reports 2007/45.

Imbens, G.W., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. J. Econ. Lit. 47, 5–86.

Innovation Norway (2018) "*Oppdragsgiverrapport fra Innovasjon Norge* 2017 (eng: Principal Report from Innovation Norway 2017)", Innovation Norway, Oslo. (https://www.regjeringen.no/contentassets/70163e970fde43eb9463c79f4def0a0e/innovasjon-norge-oppdragsrapport-2017.pdf).

Jaffe, A.B., 1998. The importance of 'spillovers' in the policy mission of the advanced technology program. J. Technol. Transf. 23 (2), 11–19.

Klette, T.J., Møen, J., Griliches, Z., 2000. Do subsidies to commercial R&D reduce market failures? Microeconometric evaluation studies. Res.Policy 29, 471–495.

Lechner, M., 2001. Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. In: Lechner, M., Pfeiffer, F. (Eds.), Econometric Evaluation of Labour Market Policies. Physica, Heidelberg, pp. 1–18.

Lechner, M., 2010. "The estimation of causal effects by difference-in-difference methods. Found. Trends Econom. 4, 165–224.

Lechner, M., 2015. Treatment effects and panel data. In: Baltagi, B. (Ed.), The Oxford Handbook of Panel Data. Oxford University Press, Oxford, pp. 257–284.

Lechner, M., Wunsch, C., 2013. Sensitivity of matching-based program evaluations to the

availability of control variables. Labour Econ. 21, 111–121.
Lokshin, B., Mohnen, P., 2013. Do R&D tax incentives lead to higher wages for R&D workers? Evidence from the Netherlands. Res. Policy 42 (3), 823–830.
chap. 2Mohnen, P., 2018. Effectiveness of direct and indirect R&D support. In: Niosi, J. (Ed.), Innovation Systems, Policy and Management. Cambridge University Press, ProQuest Ebook.
Møen, J., 2005. Is mobility of technical personnel a source of R&D spillovers? J. Labor Econ. 23 (1), 81–114.
Møen, J., 2007. R&D spillovers from subsidized firms that fail. Tracing knowledge by following employees across firms. Res. Policy 36 (9), 1443–1464.
OECD (2016) "Science, Technology and Innovation Outlook 2016", DOI: http://dx.doi.org/10.1787/sti_in_outlook-2016-en.
OECD (2018) Gross Domestic Spending on R&D (Indicator). doi: 10.1787/d8b068b4-en.
Romer, P.M., 1990. "Endogenous technological change. J. Polit. Econ. 98, S71–S102.
Rubin, D.B., 1990. Formal modes of statistical inference for causal effects. J. Stat. Plan. Inference 25, 279–292.
Sadun, R., Bloom, N., van Reenen, J., 2017. Why do we undervalue competent management? Great leadership and brilliant strategy won't succeed without operational excellence. Harv. Bus. Rev. 95 (5), 120–127.
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 J. Econ. 31 (1), 82–100.
Yu, X., Dosi, G., Lei, J., Nuvolari, A., 2015. Institutional change and productivity growth in China's manufacturing: The microeconomics of knowledge accumulation and 'creative restructuring' Ind. Corp. Change 24 (3), 565–602.