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Public R&D Support and Firms' Performance
A Panel Data Study

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Public R&D Support and Firms' Performance
A Panel Data Study

Øivind A. Nilsen, Arvid Raknerud and Diana-Cristina Iancu

Abstract:

We analyse all the major sources of direct and indirect R&D subsidies in Norway in the period 2002-2013 and compare their effects on individual firms' performance. Firms that received support are matched with a control group of firms that did not receive support using a combination of stratification and propensity score matching. Changes in performance indicators before and after support in the treatment group are compared with contemporaneous changes in the control group. We find that the average effects of R&D support among those who obtained grants and/or subsidies are positive and significant in terms of performance indicators related to economic growth: value added, sales revenue and number of employees. The estimated effects are larger for start-up firms than incumbent firms when the effects are measured as relative effects (in percentage points), but smaller when these effects are translated into level effects. Finally, we do not find positive effects on return to total assets or productivity for firms who received support compared with the control group.

Keywords: Public policy, Firm performance, Treatment effects, Stratification, Propensity score matching, Productivity

JEL classification: C33, C52, D24, O38

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1. Introduction

There is a mutual understanding among economists that technological progress is closely linked to economic growth and that it is spurred by investments in Research and Development (R&D) (see e.g. Romer, 1990). The mechanisms connecting innovation and productivity are related to both existing and new firms, and to destruction of less efficient ones. Among existing firms, R&D might show up as creation of new goods and services, leading to increased demand for the products of the firm, or to changes in the way the firm operates through process- and organizational innovations. R&D may also lead to entry of more efficient firms and new firms on the technology frontier.

If firms themselves would get the whole economic benefits of their R&D investments, there would be no need for public support of R&D in the business sector. Thus, when policy-makers emphasise the importance of public R&D support, it is based on the understanding that there are market failures and spillovers related to investments in R&D (see e. g. Griliches, 1992). A common source of market failure is knowledge externalities. Such externalities may occur if it is difficult to establish ownership rights of new production methods or technologies, enabling competitors to take advantage of investments in R&D without bearing the costs. The government might subsidize R&D investments to reduce the marginal cost of R&D and/or the perceived risk of external investors or lenders. In this way government support may lead to increased R&D and/or innovation activities (see e.g. Hall and van Reenen, 2000.)

The average gross domestic spending on R&D as percentage of GDP in the OECD countries has been quite stable over the period 2000-2016, varying from 2.1 to 2.4 (OECD 2018). At the same time OECD (2016, Figure 4.7) shows that the intensity of public support has increased as a percentage of GDP in most OECD countries over the last ten years. With this as a background, and knowing that in many countries there are several co-existent and potentially complementary support schemes, the goal of this paper is to evaluate quantitatively the economic benefits of R&D subsidies on firms' performance. The results presented are based on indirect methods where it is assumed that investments in R&D can lead to product and process innovations, which in turn can be reflected in performance indicators measured over time. The outcome variables studied are (firm-level) sales revenue, number of employees, value added, labour productivity (valued added per employee), and return on assets. These outcome variables are highly relevant from a policy perspective as the analysed subsidy instruments are intended to contribute to increased value added and employment in R&D-intensive firms.

The main novelty of this paper lies in our ability to study all the major sources of R&D subsidy programs in one country – Norway – *simultaneously*; both direct subsidies (grants) and tax credits. This is potentially of great importance, as a large share of firms that receive direct support also receive tax benefits (but *not* vice versa). Our data have two key features that we exploit: (1) we can merge firms with information about received public support over a long time period: 2003-2014, (2) the data have universal coverage of incorporated firms with detailed accounting, employment and ownership information. The combination of three contemporaneous policy instruments, the long length of the analysed period, and the possibility to link policy instruments with firm level data make our study unique compared to the existing literature. Although there are other studies that address the issue of a firm simultaneously using multiple sources of public support (e.g. Czarnitzki and Lopes-Bentoa, 2013, and Dumont, 2017), we are, to the best of our knowledge, the first to analyse all major sources of support in one country and matching these data to the whole population of (incorporated) firms.

Using panel data, we can monitor the outcome variables over time – before and after support – and compare with a control group of firms that do not receive support, i.e. firms that are representative of the counterfactual outcomes for those receiving support. The advantage of such an approach is that the outcomes are possible to measure both for the treatment group and for the control group. However, there can be a large element of randomness in such comparisons, which necessitates large datasets to distinguish systematic differences from spurious correlations. Thus, one needs both a sufficiently large treatment group and a large reference population from which one can draw the control group. If the premises of the matching are met, one can interpret the estimated effect as a causal effect of the policy instruments among the firms that actually receive support: the average treatment effect on the treated (ATT).

Our empirical findings seem to indicate the following: First, our estimates of the average effects of support are positive and significant in terms of performance indicators related to economic growth – but mostly non-significant regarding labour productivity or returns to assets. Second, there is a clear tendency that (1) the estimated effects are higher for start-up firms than for incumbent firms when the effects are measured as relative effects in percentage points, but lower when the relative effects are translated into level effects, (2) higher for the tax credit scheme and the Research Council of Norway than for Innovation Norway, and (3) that the effects increase with the amount of support. In particular, support that amounts to under NOK 500 000 (60 000 Euro)[1] have little or no effect, whatever the policy instrument.

The remainder of the paper is structured as follows: Section 2 surveys the existing literature. Section 3 presents information about the institutional setting in Norway. Section 4 presents the data. Section 5 describes the matching procedure and the general econometric model used for the analysis. Section 6 provides the main results and several sensitivity analyses, and discusses the results in light of existing findings. Finally, Section 7 concludes.

2. Exiting Literature

The issue of whether public R&D spending and government subsidies are complementary and additional to private spending or tend to crowd out private R&D has been discussed in many prior studies. A critical survey of some early microeconometric studies is given by Klette *et al*. (2000), with focus on the problem of establishing a valid control group in a non-experimental setting. Also David *et al*. (2000) are critical to the earlier literature and conclude that the many estimates of crowding out effect and input additionality found in the earlier literature are generally biased due to selection issues. The more recent microeconometric literature on the effects of public programs to spur private R&D, are generally more aware of – and explicitly address -- methodological problems. Examples include: Wallsten (2000) (U.S. firms), Duguet (2004) (French firms), Czarnitzki and Licht (2006) (German firms), Cappelen *et al*. (2012) (Norwegian firms), Lokshin and Mohnen (2013) (Dutch firms), Dumont (2017) (Belgian firms), and Dechezlepretre *et al.* (2016) (UK firms).

The most commonly used empirical framework for studying the economic impact of firms' R&D and innovation activities is the so-called CDM model. In their original paper, Crepon *et al*. (1998) propose a three-stage model. First, they specify a probit model of the decision to undertake an innovation activity. Conditional on a positive outcome of this (binary) choice, the firm chooses its R&D intensity and, finally, the economic outcome variable of interest (e.g., productivity) is analysed within a standard regression framework. Later developments and applications of the CDM framework are reviewed in Lööf *et. al*. (2017). Takalo *et al*. (2013) propose a similarly structured approach, but where the focus is on the impact of public policy: the dependent variable in the first step is a dummy of whether the firm has a project with public support or not.

[1] Based on the mean exchange rate of about 9 NOK per EURO during the period analysed.

While our model is consistent with both the three-stage CDM framework and the approach of Takalo *et al*. (2013), we use a more reduced form framework that does not require R&D or innovation data at the firm level to study the effect of R&D support on economic outcomes. In our approach, the firm decides to apply for tax credits and/or a grant; if it is accepted, the firm undertakes the project and may thereby increase its knowledge stock, which again may have positive effects on performance indicators, such as economic output or productivity. The critical prerequisite for our analyses is that our control group of firms is representative of the counterfactual outcomes for the firms that receive support (i.e., the outcomes if they had not received support). The average difference between the actual and the counterfactual (hypothetical) outcomes is the treatment effect we want to estimate.

3. Institutional setting

Since 2002, the three main government instruments to promote R&D and innovation in the business sector in Norway have been Innovation Norway (IN), the Research Council of Norway (RCN), and the R&D tax credit scheme Skattefunn (SKF). IN as we know it today, was formed through a merger of the Norwegian Industrial and Regional Development Fund, the Norwegian Trade Council, Government Consultative Office for Inventors and the Norwegian Tourist Board. IN's activities consist of district programs and innovation applications, and are mainly financed by local governments, the Ministry of Regional Development, and the Ministry of Fisheries. Our evaluation covers only the innovation programs, as the other IN-programs are not aimed at promoting R&D and innovation, but give direct support to sparsely populated areas or the agricultural sector. The innovation programs include grants, innovation loans, capital loans and advice to companies to develop a new product or new technology, or promote organisational innovations.

The tax credit scheme *Skattefunn* (SKF) was introduced in 2002 for small and medium firms (SMEs). The scheme was expanded in 2003 to include all firms. SKF is regulated by Norwegian tax law and is subject to supervision by the EFTA Surveillance Authority (ESA). Through the SKF tax credit scheme, firms get tax credits for R&D; either tax deductions or cash refunds (see below). Only approved costs provide the basis for tax deductions.[2] From 2003, the *SKF* scheme granted large firms 18 percent of R&D expenses related to an approved project up to a limit of 4 million NOK. From 2009 to 2013, the maximum limit was 5.5 million NOK. Hence, the maximum tax relief for a large firm[3]

[2] Only projects approved by the Skattefunn division of the Research Council of Norway provide a basis for tax deductions. This only applies to costs that the firms have incurred in the income year the approval was granted. The tax authorities control the stated costs and aggregate public support for the enterprise under the State Aid Code.

[3] Since then the limit has been increased several times and is now NOK 25 mill.

was about one million NOK (about 110 000 Euros). For SMEs the rate is 20 percent. The tax refund takes place the year after the actual R&D expenses have occurred (and the project was approved). If the firm's taxes are less than the refund, the remaining tax credit is given as a direct grant (see Cappelen *et al*., 2010 for more details). In fact, each year about three fourth of the total tax subsidies are given as direct grants.[4]

While SKF is a general instrument, support from the Research Council of Norway (RCN) is a selective instrument, where firms compete for funds. The main argument for a selective support scheme is that the public can direct support towards projects expected to have major positive external effects and consequently higher social than private economic return. A theoretical basis for such project selection is found in Jaffe (1998), who evaluates the potential for positive externalities (spillovers), private financial returns and additionality.

4. Data

The main data include information about the timing and amount of support from the three main R&D policy instruments: IN's innovation program, direct R&D subsidies from the RCN, and SKF – the R&D tax credit scheme. Our data cover the period 2002-2013, and are merged with firm level register data collected by Statistics Norway. The data have the advantage that they are collected for public registering and have universal coverage for limited liability companies. Furthermore, they are scrutinised by Statistics Norway before being made public. Hence, the data are in general of a high quality.

We limit the population of firms to limited liability companies (incorporated firms), since our performance indicators are based on accounting information. Incorporated firms contribute to 80-90 percent of value added in the market-based industries (the excluded industries are: primary industries, health care and the government sector), and a roughly equal share of government R&D support. Furthermore, we exclude firms with their main activity in the industry Research and Development (NACE 72). The reason is that firms in this industry receive, directly or indirectly, R&D support on a regular basis. Thus, a proper control group cannot be established.

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

In all our analyses, we distinguish between (1) support to entrepreneurial firms, defined as firms that are less than three years of age (counted from the date of incorporation) at project start and (2) support to incumbent firms.

Operationalisations

One could argue that in an ideal environment one should observe both project identifiers and the outcome variables at the project level. However, in practice, all the outcome variables are available from register data collected at the level of the firm who obtains support. Hence, some form of aggregation from the project to firm level must be made. A further complication is that tax credits are available from tax accounts data and hence refer to a *firm-year* (a firm observed in a particular year), not to a specific research project. In the lack of unique project identifiers, we have to operationalize the concept of a research project. This concept must be applicable to all forms of monetary support, and co-funding of projects by multiple instruments. In particular, we must take into consideration that most projects have a duration beyond one year: the median duration of RCN-projects is three years, and the median number of years with *consecutive* tax refunds is two years. Moreover, the same project may get support from several sources.

We proceed by making the following simplifying assumptions: (1) A project is triggered by an award. (2) The project is believed to start the year after the first occurring award (subsidy). (3) The project length is standardised to three years (the normal length of projects in the RCN). (4) If a firm gets additional subsidies during the project period of three years (regardless of source), this will be regarded as support for the same project. (5) The overall project support includes the sum of all support to the firm from all funding sources over the 3-year project period.

To classify projects according to source of funding, we identify the *main policy instrument*, defined as the main source of funding during the three-year project period. Descriptive statistics to be detailed below, show that the main policy instrument accounts for the main part of funding at the project level. For projects with either RCN or IN as the main policy instrument, tax credits is the clear secondary source of support, whereas for projects with SKF as main policy instrument, support from additional sources is almost negligible.

Given our operationalization of a research project, we estimate ATT at the *project level* for all three main policy instruments. Furthermore, we distinguish between whether the treatment was given to a start-up firm (defined as being at most 3 years old at project start-up) or an incumbent firm, and the amount of support that was given: small; less than 0.5 mill. NOK, medium; between 0.5 and 1.5 mill. NOK, or large; above 1.5 mill. NOK. Thus, there are three dimensions in our reporting of ATT estimates: (1) main policy instrument of the project, (2) firm-age of the firm at project start-up, and (3) amount of support given to the project. These operationalisations mean that, conditional on the *major source* and *total* amount of funding, public support to a given project is assumed to have the same effect regardless of the presence of secondary sources of funding. Our approach can be seen as circumventing the endogeneity issues that would arise if we included control variables indicating secondary sources of funding. The corresponding coefficient estimates (of these control variables) could reflect the quality and nature of the project, rather than the causal effect of having multiple sources of funding.[5] Our approach is also justified by Czarnitzki and Lopes-Bentoa (2013), who find that the estimated treatment effects of a regional R&D program in Belgium do not depend on dummy variables indicating the presence of a "subsidy mix".

The estimation of ATT is based on the standard approach in the treatment literature by forming a treatment group and control group by statistical matching. The control group includes firms that never get innovation related support from RCN, IN, or SKF. This group of firms consists of a selection of the reference population with observed characteristics similar to the companies that received funding. The matching method is a combination of stratified (exact) matching and propensity score matching (within each stratum). A more detailed description of the matching procedure is deferred to Section 5.

Descriptive statistics

Total R&D support from the three instruments to our firm-population during the period 2002-2014 amounts to 28 billion NOK. Table 1 reports total support from each policy instrument, both before and after matching. We see from the first four columns in Table 1 that the total amount of R&D subsidies before match is 7.9 billion NOK for IN, 9.2 billion NOK from RCN, and 10.9 billion NOK from SKF, of which a little less than 80 percent is covered by the firms in the matched sample (see the last four columns in Table 1). The total support is divided into projects that may consist of funding from several sources throughout the project duration. As explained above, we classify each project according to the main policy instrument of the project supported. For example, while total support from IN is 7.2 billion (before matching), total support to projects with IN as main policy instrument is 7.9 billion. There are two sources of the (positive) discrepancy of 0.7 billion: (1) some of the support from IN are

[5] The situation is similar to attempting to estimate the returns to investments using the project size as a control variable. The finding that, say, large investments have higher average returns than small ones, does not imply that an increase in a given (small) investment would yield a higher return.

given to projects *labelled* “RCN-“ or “SKF” (in total 1 billion), and (2) some of the support to IN-projects come from SKF (1.4 billion) or RCN (0.4 billion). The net effect is 0.7 billion.

Table 1. Support in million NOK, by main policy instrument. Before and after match

Support from	Main policy instrument							
	Before match				After match			
	IN	RCN	SKF	Total	IN	RCN	SKF	Total
IN	6 245	367	627	7 240	6 245	239	481	6 967
RCN	404	7 640	443	8 488	210	4 596	318	5 125
SKF	1 293	1 191	9 869	12 354	952	760	7 949	9 663
Total	7 943	9 198	10 940	28 081	7 408	5 597	8 750	21 755

The number of projects by year and main policy instrument is shown in Table 2. We note that there has been a substantial decrease in the number of SKF-projects compared to the first years after the extension in 2003. Regarding IN, the number of projects was nearly doubled in 2010 compared to 2008. This was the result of the government’s financial crisis stimulation package. The number of projects has remained at a much higher level also in the years after the crisis compared to the pre-crisis level, reflecting an increased importance of this instrument. In contrast, the number of RCN projects has been quite stable over time.

Table 2. Number of projects by main policy instrument

	Before match			After match		
	IN	RCN	SKF	IN	RCN	SKF
2002	209	239	100	176	186	91
2003	121	41	1 316	98	27	1144
2004	102	54	1 446	75	39	1224
2005	124	121	1 089	100	87	920
2006	140	82	978	112	50	839
2007	151	127	876	123	87	732
2008	200	126	621	154	79	524
2009	262	130	661	204	91	548
2010	421	119	723	345	77	602
2011	282	126	685	227	85	560
2012	284	110	723	212	70	600
2013	340	163	694	250	119	582
2014	336	128	740	102	64	369
Total	2972	1566	10652	2178	1061	8735

From the numbers in the three last columns of Table 2 – after match – and the corresponding numbers in Table 1, it follows that the average amount of funding per project with respectively IN, RCN, and SKF as the main policy instrument is: 3.4 million, 5.3 million, and 1.0 million.[6]

Table 3. Share of project support from each policy instrument, by the projects' main instrument. After match

Support from	Main policy instrument		
	IN	RCN	SKF
IN	0.84	0.04	0.06
RCN	0.03	0.82	0.04
SKF	0.13	0.14	0.91
Total	1.00	1.00	1.00

In the rest of this section, we focus on the after-match sample. First, in Table 3, we report the share of support coming from the main instrument versus other sources. We see that projects with IN as the main instrument, obtain 84 percent of total project support from IN, projects with RCN as the main instrument obtain 82 percent from RCN and, finally, SKF-projects receive 91% of the support from this instrument. For both IN- and RCN-projects, SKF is the largest secondary source of funding, providing between 15 and 20 percent of total public support. The relatively high share of SKF-funding among the RCN-project is not surprising, as RCN-approved R&D projects are legally entitled to tax credits (with an upper limit at the firm level due to EEA rules). On the other hand, projects with SKF as the main instrument obtain a very small share of funding from RCN (4 percent).

Table 4a. Number of projects by main policy instrument, support amount, and firm age category. After match

Main policy instrument	Start-up firms with support			Incumbent firms with support		
	Support amount (mill. NOK)			Support amount (mill. NOK)		
	Small (<0.5)	Medium	Large (>1.5)	Small (<0.5)	Medium	Large (>1.5)
IN	217	219	284	434	358	750
RCN	41	26	117	178	155	592
SKF	722	731	436	2 584	2 736	1 757
Total	980	976	837	3196	3249	3099

[6] The calculations are: 7408/2178=3.4, 5597/1061=5.3 and 8750/8735=1.0.

Table 4b. Share of support by main policy instrument, support amount, and firm age. After match

Main policy instrument	Start-up firms with support			Incumbent firms with support		
	Support amount			Support amount		
	Small (<0.5)	Medium	Large (>1.5)	Small (<0.5)	Medium	Large (>1.5)
IN	0.04	0.16	0.80	0.07	0.20	0.73
RCN	0.02	0.06	0.92	0.02	0.10	0.87
SKF	0.07	0.33	0.60	0.09	0.36	0.55

More information about the support and the recipients is given in Tables 4a and 4b, which categorizes the project support along three dimensions: (1) main policy instrument, (2) support amount (small, medium or large) and (3) firm-age (start-up or incumbent). About one fourth of the projects are given to start-up firms. Approximately one third of the projects belong to each of the support amount categories, but with considerable heterogeneity across the main policy instruments. In particular, RCN-projects have a much higher share of large projects than IN and (in particular) SKF.

Table 5. Share of project support by industry, after match

NACE	Share
Manufacturing	0.66
-Production of chemicals	0.17
-Production of chemicals rubber and plastic products	0.06
-Production of computers and el. and optical instr.	0.08
-Production of motor vehicles	0.09
Retail trade	0.04
Information and communication	0.16
Professional and scientific services	0.12
Administrative services	0.03
Total	1

Table 5 provides information about the distribution of support across industries. We see that support is highly concentrated in a few industries, with 2/3 of total support going to Manufacturing (with Production of chemicals as the largest 2-digit NACE level industry). Then comes Information and communication (16 %) and Professional and scientific services (12 %). An almost negligible share of the support goes to other industries.

5. Matching methodology

The classical matching estimator pairs the treated firms with a control group that is assumed to represent the counterfactual (non-treated) outcomes of the treated firms. The control group is selected based on a vector of matching variables, S_i, where subscript *i* denotes firm. Under certain conditions, a treated firm and the matching firms to which the treated firm is paired are identical in all respects, except a random term, ε_i. The most important condition is that the untreated outcome (the counterfactual outcome of a treated unit) is independent of treatment assignment *conditional on* S_i. This is called the Conditional Independence Assumption (CIA), often referred to as *unconfoundedness*. In our context, this means that if a firm obtains (is assigned to) R&D support in period T_i, this assignment is *per se* uninformative about the counterfactual outcome of the dependent variable (given S_{iT_i}) in the post-treatment period, T_i+1.

We will now first consider the estimation of a simplified version of our model, with a binary treatment indicator, $D_i \in \{0,1\}$, assigned at a fixed point in time, T_i (which may differ across firms). Specifically, we will consider using a combination of differencing and matching, advocated by Blundell and Costa Dias (2009).

Let $y_{it}(1)$ and $y_{it}(0)$ denote the dependent variable, the outcome of R&D support (treatment), when the (same) firm, *i*, obtains treatment and non-treatment, respectively. We assume that

$$
\begin{aligned}
y_{it}(1) &= f_i + m_t(S_{it}) + \tau_i \cdot 1(t > T_i) + \varepsilon_{it1} \\
y_{it}(0) &= f_i + m_t(S_{it}) + \varepsilon_{it0}
\end{aligned}
$$

where f_i is a fixed firm effect, $m_t(S_{it})$ is a non-parametric (unknown) *common trend function*, τ_i is the firm-specific treatment effect and $1(A)$ is the indicator function which is one if the statement *A* is true and zero otherwise. The vector S_{it} consists of a "minimal" set of observable variables that makes both error terms $E(\varepsilon_{it0} \mid S_{it}) = 0$ and $E(\varepsilon_{it1} \mid S_{it}) = 0$. The realized (observed) value of y_{it} is then $y_{it}(D_i)$. Thus, if $D_i = 0$, neither $y_{it}(1)$ nor the assignment year, T_i, are observed.

The inclusion of the common trend function $m_t(S_{it})$ in the model of $y_{it}(D_i)$ is important as the treatment group and the control group (the non-treated outcomes) must have the same trend. By including $m_t(S_{it})$, we mitigate the potential problem that the observed (pre-treatment) characteristics, S_{iT_i}, which determine the treatment assignment may also influence the outcome variable, $y_{i,T_i+1}(D_i)$. Based on the above model, we can formally define the average treatment effect on the treated (ATT):

$$ATT = E(y_{i,T_i+1}(1) \mid D_i = 1) - E(y_{i,T_i+1}(0) \mid D_i = 1)$$

Here $E(y_{i,T_i+1}(1) \mid D_i = 1)$ is the expected (post-treatment) outcome for firms in the treated group, i.e. those who were assigned to R&D support at time T_i. This means that the post-treatment outcome, $y_{i,T_i+1}(1)$, is observable for all firms in this group. On the other hand, $y_{i,T_i+1}(0)$ is not observed if D_i = 1. Using the mean outcome of the firms that do not get R&D support: $E(y_{i,T_i+1}(0) \mid D_i = 0)$ may not be appropriate for estimating $E(y_{i,T_i+1}(0) \mid D_i = 1)$. This non-interchangeability of $E(y_{i,T_i+1}(0) \mid D_i = 0)$ and $E(y_{i,T_i+1}(0) \mid D_i = 1)$ is due to the fact that characteristics that determine whether a firm gets R&D support are also likely to determine the future outcome of this firm. To deal with this potential effect, often referred to as the selection effect, we combine stratification and propensity score matching.[7]

The specific motivation for stratification in our case is that cell characteristics are key determinants of both the probability of obtaining support, e.g. through regional programs and programs targeting young firms, and of the dependent variables, e.g. through industry-specific market conditions and local labour market conditions.[8] More specifically, we do as follows: First, in any given year *t*, we stratify firms into industry–region–age cells (j, r, s) consisting of firms that belong to 2-digit NACE industry *j*, region *r* and age group *s* (*1-3, 4-6, 7-9*, or *>9* years old). Next, within these industry-region-age specific cells, we construct a *continuous* matching variable, S_{it}, which in our application is a measure of the firms' size (total assets).

Now, within each stratum we use propensity score matching to match treated and non-treated firms using the matching variable, S_{it}. The probability of treatment given S_{iT_i}: $P(S_{iT_i}) = \Pr(D_i = 1 \mid S_{iT_i})$ is

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[7] See the seminal contribution by Rosenbaum and Rubin (1983) who effectively reduced the multi-dimensional matching problem to a univariate one, by matching on the probability of treatment given S_{iT_i}: $P(S_{iT_i}) = \Pr(D_i = 1 \mid S_{iT_i})$.

[8] A general discussion of the pros and cons of matching with stratification are discussed in Caliendo and Kopeinig (2008).

the so-called propensity score. Moreover, the log-odds $P(S_{iT_i})/(1-P(S_{iT_i}))$ is a non-linear function of S_{it}, specified as a piecewise linear spline. The kink points of the spline are located at the quartiles of the (cumulative) empirical distribution of the size variable (specific to each strata).

The propensity score we estimate is a *transition probability*: the probability of transition at T_i from previously having had no support, to obtaining first-time support from either IN, RCN, or SKF. The estimated propensity score of each firm in the group of treated firms is then matched with one or more of the nearest neighbours. See Appendix A for technical details. The matching procedure used is the STATA routine *psmatch2* with 1 to 5 nearest neighbour matching with trimming.[9]

The combination of stratification and propensity score matching yield a sample of comparable *matched* firms with an approximately *balanced* distribution of the observed characteristics, i.e. when we compare this distribution for the group of firms receiving R&D support and the group of matched firms *not* receiving such support. By further combining this matching procedure with a difference-in-difference approach (DID), we are able to control for unobserved firm specific effects, f_i.[10] The classical DID estimator when applied to a matched sample, can be expressed as:

$$DID = \frac{1}{\# N^T} \sum_{i \in N^T} \left(\Delta y_{i,T_i+1} - \frac{1}{\# C(i)} \sum_{j \in C(i)} \Delta y_{j,T_i+1} \right)$$

where N^T is the set of treated firms, $C(i)$ is the control group of firms matched to firm $i \in N^T$ and $\#A$ denotes the number of elements in (any set) A. The estimation strategy is to contrast each post-treatment outcome, $\Delta y_{i,T_i+1}$, in the treatment group, with the average outcome in the control group $C(i)$ (the firms matched to the treated firm i):

[9] We use the command: *psmatch2 common trim(10)*. This imposes a common support by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. It also drops 10 percent of the treatment observations at which the propensity score density of the control observations is lowest. See Leuven and Sianesi (2003) for documentation.

10 It is an ongoing debate in the literature whether one would benefit from combining the two approaches; see for instance Blundell and Costa Dias (2009), Imbens and Wooldridge (2009), Lechner (2010), and Chabé-Ferret (2015). We emphasise the argument used by Blundell and Costa Dias (2009, p. 604); "… the combination of matching with DID as proposed in Heckman *et al*. (1997) can accommodate unobserved determinants of the nontreated outcome affecting participation for as long as these are constant over time."

$$\frac{1}{\#C(i)}\sum_{j\in C(i)}\Delta y_{j,T_i+1}.$$

The DID estimator is given as the average over these contrasts (differences) over all the treated firms $i \in N^T$.

Above we have assumed that any effect of a treatment assigned in T_i is realized immediately afterwards (in $T_i + 1$). However, in our application we have annual data (*t* is a calendar year), while treatment effects are naturally defined over longer time intervals, from project start (T_i) to project end or later ($T_i + k$, $k \geq 3$). If $k = 3$ (the project length), the average treatment effects of the treated is modified as follows:

$$ATT = \sum_{k=1}^{3}\left(E(\Delta y_{i,T_i+k} \mid i \in N^T) - E\left(E(\Delta y_{j,T_i+k} \mid j \in C(i)) \mid i \in N^T\right)\right)$$

(cf. the expression for DID above).

To estimate ATT we apply a regression formulation of the DID estimator (see Lechner, 2010), rather than the classical DID estimator stated above. The regression formulation is:

$$\begin{aligned}\Delta y_{it} &= m_{C(i),t} + \tau_{iT_i} 1(T_i < t \leq T_i + 3)/3 + \Delta\varepsilon_{it1}, \text{ for } \forall i \in N^T,\\ \Delta y_{jt} &= m_{C(i),t} + \Delta\varepsilon_{jt0}, \text{ for } \forall j \in C(i).\end{aligned}$$

where the error term is assumed to have a moving average (MA(q)) distribution. The division by 3 in the expression above means that τ_{iT_i} can be interpreted as the 3-year change in y_{it} induced by the treatment. The treatment effects at the firm-level (τ_{iT_i}) are allowed to be project-specific, implying $ATT = E\left(\tau_{iT_i} \mid i \in N^T\right)$. Note that the expressions for Δy_{it} include interaction terms between time dummies and cell membership, where the (cell-specific) common trend is:
$m_{C(i),t} = E(\Delta m_t(S_{jt})) \mid j \in C(i))$.

As pointed out by Lechner (2010), there are several advantages of the regression formulation of the DID identification and estimation problem – and, in fact, no disadvantages when control variables are *not* included (*ibid* p. 195), as in our case. The first advantage is the easiness of obtaining the final estimates and their standard errors. Second, the regression formulation naturally extends to an arbitrary choice of treatment interval. For example, we will examine "long-term" effects from project *end* to three years after project end, i.e. from $T_i + 3$ to $T_i + 6$. Third, the regression formulation easily accommodates more treatments. This is important to us, as many firms *do* obtain repeated support. To accommodate repeated treatments, we replace T_i with $T_i^{(k)}$ – the year of the *k*'th treatment assignment – in the regression equation. Note that, by definition, a new project cannot overlap with the preceding project: $1 \leq T_i^{(1)} + 3 \leq T_i^{(2)} + 3 \leq \ldots$.

6. Empirical results

Assessing the matching quality

The comparisons in Table 6 show that the median values of the outcome variables for the treatment and the control groups are similar at the time of matching (for the matched non-treated firms we do not separate between amount of support given to the corresponding treated firms). This ensures that the balancing properties of the matching hold.

Figure 1 depicts the distributions of the estimated propensity scores in the treated and matched group of firms after the matching. The extreme values (minimum and maximum) of the propensity scores are trimmed to ensure that the common support condition is met. The results indicate that the distributions of the treated and the control groups are very similar.

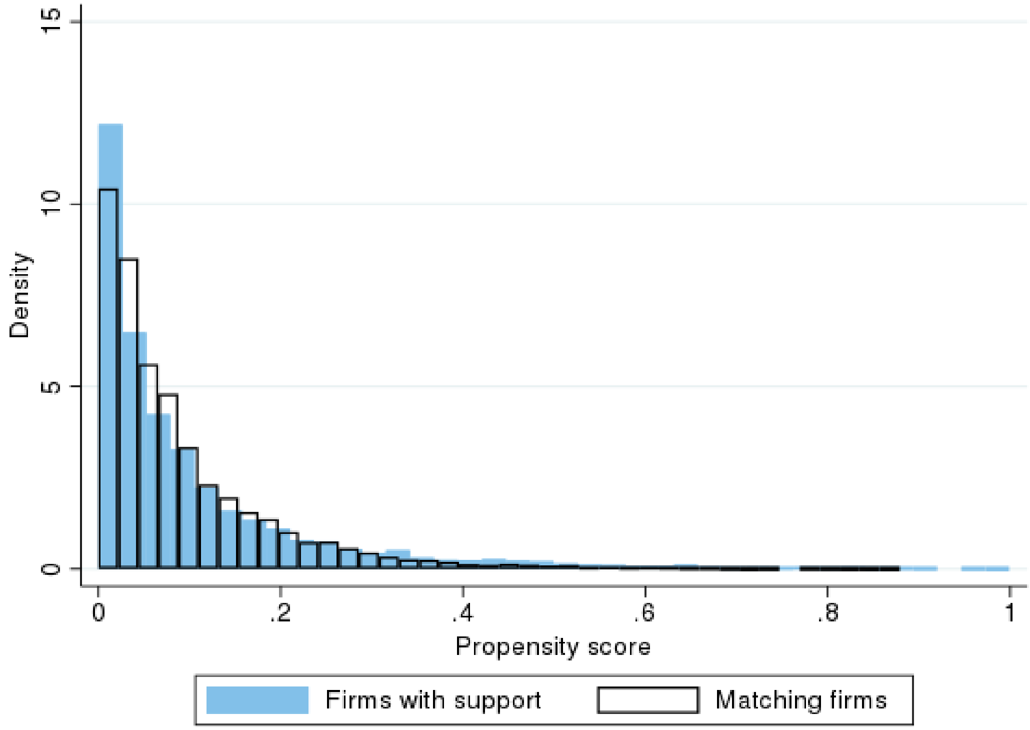
Estimates of relative ATT

In our application, the dependent variable, y_{it} ,denotes either: (1) log of sales revenue, (2) log of number of employees, (3) log of value added, (4) log-labour productivity (value added per employee), or (5) return on total assets. Thus, Δy_{it} is approximately equal to the annual relative change in y_{it}.

Table 6. Median values of outcome variables at the year of matching, by amount of project support and main policy instrument

		Treated group						Control group
		Before matching			After matching			Matched firms
		Support amount (mill. NOK)			Support amount (mill. NOK)			
Main policy inst. – Outcome variable	Age Category	Small (<0.5)	Medium (0.5-1.5)	Large (>1.5)	Small (<0.5)	Medium (0.5-1.5)	Large (>1.5)	
IN – No. of employees								
	Start-up	2	2	5	2	2	4	3
	Incumbent	8	8	15	7	6	11	9
IN – Value added per employee								
	Start-up	216	251	142	190	236	144	241
	Incumbent	382	390	410	379	362	397	405
IN – Return on total assets								
	Start-up	3 %	0 %	-2 %	2 %	-1 %	-6 %	0 %
	Incumbent	6 %	6 %	5 %	6 %	3 %	5 %	6 %
RCN – No. of employees								
	Start-up	5	8	12	2	3	4	3
	Incumbent	19	49	81	6	18	14	12
RCN – Value added per employee								
	Start-up	300	362	381	261	439	263	306
	Incumbent	422	444	515	451	503	520	461
RCN – Return on total assets								
	Start-up	-9 %	4 %	2 %	-6 %	7 %	-1 %	1 %
	Incumbent	7 %	11 %	6 %	9 %	14 %	3 %	8 %
SKF – No. of employees								
	Start-up	4	5	7	3	4	6	4
	Incumbent	11	15	21	8	11	14	11
SKF RCN – Value added per employee								
	Start-up	341	376	345	345	378	375	329
	Incumbent	408	421	489	399	407	467	428
SKF – Return on total assets								
	Start-up	8 %	7 %	4 %	11 %	7 %	4 %	5 %
	Incumbent	11%	11 %	9 %	11 %	12 %	9 %	9 %

Figure 1: Distribution of propensity scores among treated and matched firms



Tables 7-10 show the estimated treatment effects in percentage points over the three-year period from project start, T_i, to $T_i + 3$, i.e. the average three-year growth difference between the treated and matched firms. When presenting the results below, we distinguish between different treatment groups according to the following characteristics of the supported project: (1) main policy instrument of the project (IN, SKF or RCN); (2) start-up firm (maximum three years old at project start) or incumbent firm; and (3) amount of project support (small, medium or large). This yields in total $3 \times 2 \times 2 = 12$ possible combinations. Each of these combinations constitute a specific treatment group, N^T. To simplify notation, ATT will denote the average treatment effect regardless of what treatment group is considered (this will be clear from the context).

Table 7 presents average treatment effects (ATT) for each combination of main policy instrument and age group and does not distinguish between amounts of support. First, let us clarify the interpretation of the figures in the table by focusing on an example: growth in the number of employees for start-up firms receiving support from IN. According to Table 7, such firms will have 21.4 percentage points additional increase in headcount three years after project start compared with not receiving any support. This is a statistically significant estimate at the 0.1 percent level (as indicated by ***). For incumbents, the corresponding estimated additional increase (ATT) is much smaller – 2.4 percentage points – which is not significant even at the 5 percent level.

Table 7. Estimated ATT, by main policy instrument and firm age category. Three-year differences in percentage points[1]

Outcome indicator	Age category	Main policy instrument					
		IN		RCN		SKF	
		Effect	z	Effect	z	Effect	z
Sales	Start-up	41.35 ***	5.44	39.98 *	2.56	33.32 ***	7.56
	Incumbent	8.56 *	2.52	9.27 *	2.06	16.27 ***	10.58
No. of employees	Start-up	21.36 ***	5.25	24.80 **	3.16	11.63 ***	4.92
	Incumbent	2.47	1.26	-3.93	-1.55	5.55 ***	6.15
Value added	Start-up	14.29	1.89	41.60 **	3.11	25.10 ***	6.39
	Incumbent	5.51	1.76	10.65 **	2.75	11.91 ***	9.09
Labor productivity	Start-up	-5.03	-0.79	28.07 *	2.52	9.38 **	2.91
	Incumbent	1.93	0.86	3.92	1.44	3.92 ***	4.34
Return on assets	Start-up	1.41	0.98	1.07	0.42	0.85	1.05
	Incumbent	-0.68	-1.24	0.10	0.16	0.32	1.36

[1] Additional growth in percentage points during the three-year period from project start (year T_i) to project end (T_i+3). *, ** and *** denote significant estimates at 5, 1 and 0.1 percent level, respectively

There are three main takings from the numbers in Table 7. First, sales growth is the only indicator with significant estimates across all the policy instruments and age groups. Second, all policy instruments lead to significant increases in employment among start-up firms. Third, none of the instruments improves returns on assets. Looking at the results in Table 7 in more detail, we note the following: (1) The estimates for start-up firms across all the main policy instruments indicate significant estimates of 30-40 percentage points increase in sales revenue (over three years), and 10-15 percentage points increase in employment. (2) The estimated ATT for incumbent firms is significant for all the instruments regarding sales revenue (8-16 percentage points estimated increase), but only support from SKF has a significant positive effect on employment (5 percentage points estimated increase). (3) Comparing start-up firms vs. incumbent firms, support from SKF leads to approximately 25 vs. 10-percentage points increase in value added and 10 vs. 5-percentage points increase in labour productivity. (4) The corresponding results with regard to support from RCN are of a similar magnitude as for SKF, but less significant. (5) Support from IN does not seem to have any significant effects on incumbent firms, although the estimates for value added are close to being significant at the 5 percent level.

The main policy instruments

Tables 8-10 present results for each of the three main policy instruments along *two* dimensions: (1) amount of support (small – less than 0.5 mill. NOK, medium – between 0.5 and 1.5 mill. NOK, or large – above 1.5 mill. NOK) and (2) age-group.

Table 8. Estimated ATT for Innovation Norway, by firm age category and amount of support.[1] Three-year differences in percentage points[2]

Outcome indicator	Age category	Support amount (mill. NOK)								
		Small (<0.5)			Medium (0.5-1.5)			Large (>1.5)		
		Effect		z	Effect		z	Effect		z
Sales	Start-up	4.49		0.33	18.89		1.42	88.76	***	7.33
	Incumbent	0.20		0.03	-0.02		0.00	17.65	***	3.58
No. of employees	Start-up	4.56		0.58	-0.39		-0.05	47.14	***	7.71
	Incumbent	4.27		1.12	-2.58		-0.65	3.88		1.39
Value added	Start-up	20.90		1.64	-4.59		-0.35	26.19	*	2
	Incumbent	1.26		0.22	5.64		0.91	7.91		1.68
Labor productivity	Start-up	16.24		1.5	-25.68	*	-2.3	-6.88		-0.63
	Incumbent	-0.51		-0.12	5.40		1.2	1.54		0.45
Return on assets	Start-up	5.80	*	2.19	-5.11		-1.96	3.14		1.4
	Incumbent	0.10		0.09	-0.79		-0.71	-1.02		-1.29

[1] Projects with IN as main policy instrument.

[2] Additional growth in percentage points during the three-year period from project start (year T_i) to project end (T_i+3").

Note: *, ** and *** denote significant estimates at 5, 1 and 0.1 percent level, respectively

Results for IN-firms are reported in Table 8. We see that small or medium amounts of support have a marginal or even non-existing effect, while large amounts of aid given to start-up firms increase sales revenue, employment and value added with respectively 88, 47 and 26 percentage points according to our estimates. The results for incumbent firms are generally insignificant also for large amounts of support, except with respect to sales revenue (the estimated 18 percentage points of additional growth is significant at the 0.1 percent level).

Table 9 reports the effects on the RCN-supported projects. Again, we find that small or medium amounts of support have only a marginal or non-existing effect. For large amounts given to start-up firms, the results show strong and significant effects for the outcome indicators sales revenue, number of employees, value added and labour productivity (more than 40 percentage points additional growth on all these indicators). On the other hand, for incumbent firms the estimates are generally insignificant also for large amounts of support. The only exception is with respect to value added, where the estimated ATT of 12 percentage points is significant at the 5 percent level.

Table 9. Estimated ATT for Research Council of Norway, by firm age category and amount of support.[1] Three-year differences in percentage points[2]

Outcome indicator	Type of firm	Support amount (mill. NOK)								
		Small (<0.5)		Medium (0.5-1.5)			Large (>1.5)			
		Effect	z	Effect		z	Effect		z	
Sales	Start-up	39.64	1.13	24.02		0.66	44.83	*	2.31	
	Incumbent	4.60	0.45	22.78	*	2.17	6.57		1.14	
No. of employees	Start-up	-27.76	-1.47	14.40		0.77	41.05	***	4.29	
	Incumbent	-2.46	-0.42	-0.76		-0.13	-5.42		-1.68	
Value added	Start-up	19.47	0.68	-6.20		-0.22	68.78	***	3.88	
	Incumbent	4.71	0.52	10.82		1.23	11.93	*	2.38	
Labor productivity	Start-up	32.12	1.32	-18.87		-0.82	45.90	**	3.11	
	Incumbent	9.58	1.38	-0.59		-0.09	3.82		1.10	
Return on assets	Start-up	7.71	1.33	1.88		0.31	-1.03		-0.32	
	Incumbent	2.59	1.61	0.72		0.46	-0.75		-0.89	

[1] Projects with RCN as main policy instrument.

[2] Additional growth in percentage points during the three-year period from project start (year T_i) to project end (T_i+3”).

Note: *, ** and *** denote significant estimates at 5, 1 and 0.1 percent level, respectively

Table 10 reports effects of the tax credit scheme SKF. Here we find statistically highly significant effects of large subsidies with respect to all outcome indicators, except return on total assets, where there is no effect in the case of incumbent firms. There also seem to be some statistically significant benefits of small (<0.5 million) and medium amounts of support (0.5-1.5 mill.) of this funding alternative, although there is a clear tendency that the effects increase with the amount of support given. Again, support given to start-up firms yields higher additional growth in percentage points than support given to incumbent firms.

To examine the robustness of our results, Table 11 presents corresponding results as in Table 7 over the three-year period from project *end* to 3 years later (that is, from year $T_i + 3$ to year $T_i + 6$). These long-term effects are generally close to zero and insignificant, although there are some estimated effects that are significant at the 1 or 5 percent level. To summarize, there is no clear tendency for the effects to appear after the three-year project interval. Equally important is that we find no tendency of mean reversion: that gains achieved during the first 3-year interval are reversed during the next three years.

Table 10. Estimated ATT for SKF, by firm age category and amount of support.[1] Three-year differences in percentage points[2]

Effectindikator	Type foretak	Support amount (mill. NOK)								
		Small (<0.5)			Medium (0.5-1.5)			Large (>1.5)		
		Effect		z	Effect		z	Effect		z
Sales	Start-up	10.19		1.45	38.05	***	5.54	63.48	***	7.06
	Incumbent	7.81	**	3.14	15.48	***	6.35	28.88	***	9.94
No. of employees	Start-up	5.01		1.29	10.34	**	2.84	23.81	***	5.06
	Incumbent	3.32	*	2.27	3.65	*	2.58	11.27	***	6.68
Value added	Start-up	17.25	**	2.84	21.33	***	3.48	48.60	***	5.66
	Incumbent	8.20	***	3.85	11.07	***	5.27	18.14	***	7.16
Labor productivity	Start-up	10.21	*	2.05	3.92		0.78	18.55	**	2.65
	Incumbent	4.52	**	3.01	3.27	*	2.23	4.07	*	2.34
Return on assets	Start-up	0.44		0.34	-0.54		-0.42	4.06	*	2.4
	Incumbent	0.67		1.73	-0.10		-0.25	0.44		0.99

[1] Projects with SKF as main policy instrument.

[2] Additional growth in percentage points during the three-year period from project start (year T_i) to project end (T_i+3").

Note: *, ** and *** denote significant estimates at 5, 1 and 0.1 percent level, respectively

Table 11. Estimated ATT measured from 3 to 6 years after project start, by main policy instrument and firm age category.[1] Three-year differences in percentage points

Outcome indicator	Age category	Main policy instrument					
		IN		RCN		SKF	
		Effect	z	Effect	z	Effect	z
Sales	Start-up	77	0.69	-0.08	-0.01	7.44	1.91
	Incumbent	-4.47	-0.89	-12.77	-1.74	-2.09	-1.00
No. of employees	Start-up	11.15 *	2.52	2.44	0.35	0.98	0.43
	Incumbent	-4.45	-1.52	-7.43	-1.79	-2.91 *	-2.41
Value added	Start-up	5.08	0.65	-13.75	-1.11	7.08	1.85
	Incumbent	-15.09 **	-3.10	-6.56	-0.97	-3.49	-1.82
Labor productivity	Start-up	1.73	0.27	-7.27	-0.78	3.78	1.29
	Incumbent	-3.66	-0.96	-1.21	-0.23	0.48	0.33
Return on assets	Start-up	2.08	1.52	-4.68 *	-2.32	0.84	1.24
	Incumbent	-0.91	-1.04	-2.33	-1.95	-0.65	-1.86

[1] Additional growth in percentage points during the period from project end ($T_i + 3$) to three years later ($T_i + 6$). Note: *, ** and *** denote significant estimates at 5, 1 and 0.1 percent level, respectively

From percentage points to level effects

To say something about the estimated effects when converted into level effects, we attempt to estimate the impact per million NOK in project support for a "representative firm" for each of the 12 treatment groups. How to define such a firm is, however, far from obvious. One possibility is as the *median firm*

Table 12. Characteristics of the representative firms in each treatment group[1)]

Main policy inst. – Outcome indicator	Age category	Before matching: Support amount (mill. NOK) Small (<0.5)	Medium (0.5-1.5)	Large (>1.5)	After matching: Support amount (mill. NOK) Small (<0.5)	Medium (0.5-1.5)	Large (>1.5)
IN – No. of employees							
	Start-up	5	7	24	3	3	11
	Incumbent	29	37	51	18	14	24
IN – Value added per employee							
	Start-up	319	359	375	334	308	92
	Incumbent	427	445	477	417	508	238
IN – Return on total assets							
	Start-up	-1.26	-1.11	-0.28	-1.09	-8.04	-13.83
	Incumbent	5.90	6.81	3.74	8.78	6.89	-5.43
RCN – No. of employees							
	Start-up	40	94	228	14	7	7
	Incumbent	112	206	605	20	57	44
RCN – Value added per employee							
	Start-up	1197	380	1012	361	494	273
	Incumbent	1696	736	1142	902	404	574
RCN – Return on total assets							
	Start-up	14.74	1.57	12.02	3.78	2.53	-11.18
	Incumbent	25.01	11.89	11.72	6.62	0.30	7.70
SKF – No. of employees							
	Start-up	17	19	36	6	9	12
	Incumbent	37	57	68	23	27	29
SKF RCN – Value added per employee							
	Start-up	319	422	537	393	426	421
	Incumbent	575	490	813	505	434	527
SKF – Return on total assets							
	Start-up	1.32	2.63	6.06	5.32	0.74	-0.82
	Incumbent	10.00	9.06	11.19	13.17	7.63	7.61

[1)] Weighted average over firms within each treatment group at project start, with weights proportional to amount of support

in each treatment group, as defined by the median values described in Table 6. The weakness of this approach is that equal weight is given to all the firms in a given treatment group (e.g. in the group of start-up firms, with small amount of support and SKF as main policy instrument), regardless of how much support each firm in that group received. Therefore, we have chosen to construct a representative firm within each treatment group as a weighted average firm (at project start-up) where the weight is proportional to the amount of support given to the project. The characteristics of the representative firms are shown in Table 12.

If we compare the "representative firms" reported in Table 12, with the "median firms" reported in Table 6, we see that the former is much larger as measured by number of employees (large firms get more support). This applies to all policy instruments, especially for firms within the treatment groups with large amounts of support. We further see that firms with large IN-funded projects score lower on the outcome indicators value added per employee and return on total assets than do firms with RCN- and SKF-projects.

To estimate the level effect (or "return") to a given support scheme, we initially estimate level effects per million in project support to the representative firm within each treatment group. This is done by combining the percentage points effect estimates from Tables 8-10 with the initial characteristics of the representative firm in each treatment group (see Table 12). Finally, given these level-estimates of treatment effects, we calculate the weighted-average level-effect for each main policy instrument as follows: the estimated level-effect in each category is weighted with its share of total amount of support, as reported in Table 4b. All these calculations were done separately for incumbent and start-up firms. We can then interpret the result as an expression of the "return" on a representative project portfolio consisting of *either* incumbent or start-up firms for the given main policy instrument (6 portfolios in total). Each of the portfolios (e.g. support to start-up firms by IN) then consists of a million NOK being allocated to small, medium and large projects in accordance with the six portfolio-specific distributions in Table 4b. The final results are shown in Table 13.

Table 13. Estimated effects in levels (numbers or NOK) per million NOK in project support. Three years after project start, by main policy instrument and firm age category

Output-indicator	Age category	IN Effect	IN Conf.intervall[1)]		RCN Effect	RCN Conf.intervall[1)]		SKF Effect	SKF Conf.intervall[1)]	
No. of employees										
	Start-up	0.8	0.6	1.0	0.0	-0.5	0.5	1.1	0.8	1.5
	Incumbent	0.7	0.2	1.3	1.9	0.0	3.7	1.7	1.2	2.2
Value added (in mill. NOK)										
	Start-up	0.0	-0.0	0.1	0.2	-0.2	0.5	0.8	0.5	1. 0
	Incumbent	0.3	0.0	0.5	1.7	0.1	3.3	1.8	1.3	2.2
Value added per employee (in 1000 NOK)										
	Start-up	-1.0	-13.0	11.0	27.0	-20.0	75.0	10.0	-14.0	33.0
	Incumbent	18.0	4.0	32.0	-1.0	-38.0	35.0	16.0	3.0	29.0

[1] Lower and upper boundary in 95 % confidence interval

From Table 13 we see that the effect of a subsidy is significantly positive for all three main instruments when it comes to employment growth and value added for incumbents: Our point estimates suggest that the average effect of 1 million NOK in project support from IN to incumbent firms is 0.7 new employees and 0.3 million NOK in increased value added after three years. The corresponding estimates for RCN and SKF are significantly higher; respectively, 1.9 and 1.7 new employees and 1.8 million added growth. For start-up firms, the estimated effects per million in support are more modest. For IN and SKF, we estimate that the number of employees increases by, respectively, 0.8 and 1.1 per million NOK in support, while we find no significant effects of support from RCN. We note further that value added for start-up firms does not increase significantly either for IN or RCN support, while the increase is estimated to 0.8 million NOK per year and is significantly positive for SKF. Finally, we do not find significantly increased value added per employee (labour productivity) for any of the three instruments.

What constitutes an adequate "return" of support is generally difficult to say when we are not talking about financial returns, but total value added (reward to labour and capital). In particular, it is difficult to estimate the opportunity cost of employed labour. One must also take into account administrative costs, which are significantly higher for RCN and IN than SKF. Note that the level estimates in Table 13 are calculated on the assumption of a common treatment effect in percentage points per monetary unit in all the 12 treatment groups. Thus, the confidence intervals in Table 13 do not incorporate heterogeneity in treatment effects *within* each category. We see that the confidence intervals for the level estimates are sometimes very wide – this is especially true for the RCN. Thus, the statistical uncertainty is substantial. Nevertheless, these figures give a good indication of the magnitude we are talking about when the relative effect estimates are interpreted.

Most of the existing literature has been concerned with input additionality and crowding out effects of public support to R&D (following Bloom *et al*., 2002), or with direct innovation outcomes such as patenting (see e.g. Cappelen *et al*., 2012). There is less empirical evidence with regard to economic outcomes in general, such as growth in value added, productivity and profitability. In particular, we are not aware of any comparative analysis of different support programs that attempt to quantify the causal effect of each of them.

The existing literature indicate a positive correlation between R&D tax incentives and productivity (Cin *et al*., 2017). According to our findings, however, one should be careful about interpreting such correlations as evidence of causal effects. Lokshin and Mohnen (2013) and Moretti and Wilson (2014) find positive effects of R&D support programs on employment growth, which is in line with our findings. Some exiting analyses have distinguished between the impact of public support to R&D on small and large firms. These studies generally find stronger effects on small firms than on large firms (e.g. Baghana and Mohnen, 2009; and Castellacci and Lie, 2015). This in line with our estimates of *relative* effects, since we get larger relative effect estimates for start-up firms than for incumbent firms (that is, effects measured in percentage points). However, these differences do not translate into larger *level* effects (e.g., in terms of number of employees or value added in NOK), which we estimate to be generally larger for incumbent firms than for start-up firms.

7. Concluding remarks

Research and development (R&D) investment is considered to be one of the main drivers of technological progress and economic growth. However, due to market failures, there is ample support among policy makers and academics for increased public R&D expenditures. In many countries, including Norway, where the data for this analysis come, there are several co-existent and potentially complementary support schemes. In this paper, we therefore analyse all the major sources of direct and indirect R&D subsidies simultaneously and compare their effects on individual firms' performance. The three main schemes in Norway are analysed: innovation-oriented policies of Innovation Norway (IN), instruments of the Research Council of Norway (RCN), and the Norwegian R&D tax incentive scheme (SKF). Even though the targeted firms, their construction, and magnitude of support are somewhat different, all these schemes are meant to promote product or technology innovations. The empirical analyses are based on models from the treatment evaluation literature, matching a treated group of firms with an appropriate control group. Our analysis is made possible by our rich data set which enables us to link firm identifiers with records of received public support over a rather long period: 2003-2014. Furthermore, our data have universal coverage of incorporated firms and contain detailed accounting, employment and ownership information.

The estimates of the average effects of support from IN (the innovation program) and SKF are positive and significant in terms of percentage points growth in number of employees, sales revenue and value added, but mostly non-significant with respect to labour productivity and return on total assets. For RCN we find generally less significant effects than for IN and SKF, but this can be explained by the fact that our matching procedure finds comparable firms for a small number of RCN firms. Results for RCN are therefore representative of a much smaller percentage of the RCN project portfolio (about 1/5 of the total grant amount) than is the case for IN and SKF (about 2/3 of the amount of support). Regardless of policy instrument, there is a clear tendency that the estimated effects increase with the amount of support. Support amounts under 500 000 NOK have little or no effect, whatever the instrument, while support amounts between 500.000 and 1.5 million NOK from RCN and IN have little or no effect. This applies whether the effects are measured three or six years after project start.

For incumbent firms we find that the estimated level effects regarding the performance indicators employment and value added growth are significantly positive for all three main instruments. The estimates suggest that the average effect of 1 million NOK in project support from IN is approximately 0.8 additional employees and 0.3 mill. NOK in increased value added after three years. The corresponding estimates for the RCN and SKF are significantly higher: respectively, 1.9 and 1.7 additional employees and 1.8 million added growth. For start-up firms, we find effects that are more modest. For IN and SKF, we estimate that the number of employees increases, respectively by 0.8 and 1.2 per million in funding. We find no significant effects on the number of employees of support from RCN. Neither support from IN nor from RCN contributes to significant effects with respect to value added, but the effect is significant for a typical start-up firm receiving SKF subsidies and is estimated to be 800 000 NOK in increased value added during 3 years per million NOK in funding.
The rather modest or even insignificant returns to small amounts of R&D support might indicate that all the three schemes should be reallocated and concentrated instead of distributing small amounts to a large number of firms. Note however, that our analysis is not a cost-benefit analysis where also administrative costs are taken into account. Such a more extensive and broader analysis should be addressed in future work. When we find that start-up firms seem not to benefit from the existing support schemes, it might call for alternative schemes, better screening, or forming of new schemes that are better able to target the profitable and social beneficiary projects. Since government funding and therefore the sustainability of the welfare states both in Norway and most industrialized countries are under severe pressure in the years to come, further economic growth is likely to depend increasingly on R&D investments and innovation activities in the industries. Thus, increased knowledge about the efficiency and accuracy of the various R&D schemes are essential.

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Appendix A: The matching

For any treated firm: $T_i = T_i^{(1)}$ (the year of first-time support). Furthermore, let $M(n) = (m(1),...,m(n))$, where $n \geq 1$ is the number of treatments and $m(k)$ is a vector of characteristics of the *k*'th treatment (we will return to this below). The realized treatments of firm *i* as of year *t* is denoted $M_i(N_{it}) = (m_i(1),...,m_i(N_{it}))$ ($M_i(0)$ denotes no treatment). Note that treatments are multidimensional; not only may there be several treatments ($N_{it} > 1$), but the characteristics of the treatments may differ (source and amount of funding. etc.).

Define the treatment group $N_{jrs}^T(t)$ as the group of firms that obtained first-time support of a project in year t and belong to the cell (j,r,s) and let $C(i,t)$ denote the cell of firm *i* at *t*.. The corresponding control group is denoted $N_{jrs}^C(t)$ and is obtained by matching firms in $N_{jrs}^T(t)$ to non-treated firms in the same cell in year t. Then define $N_{jrst}{}^T$ and $N_{jrst}{}^C$ as the union over *t* of, respectively $N_{jrs}^T(t)$ and $N_{jrs}^C(t)$

Note that a firm can belong to N_{jrs}^C only if it obtained *no* support during the *whole* observation period. Furthermore, define

$$\lambda_{jrst}(M(n)) \equiv \Pr(M_i(N_{iT}) = M(n) \mid C(i,t) = (j,r,s), T_i^{(1)} = t)$$

It follows from Lechner (2001) that $P_{jrst}(S_{it})$ will be a balancing score for $M_i(N_{iT})$ if the following condition holds:

$$\Pr(M_i(N_{iT}) = M(n) \mid \mathrm{S}_{it}, C(i,t) = (j,r,s), T_i^{(1)} = t) = \lambda_{jrst}(M(n))$$

That is, how many treatments a firm gets – or their characteristics – given that it obtains the first treatment at *t*, do not depend on the matching variables, S_{it}. It follows that

$$\Pr(M_i(N_{iT}) = M(n) \mid \mathrm{S}_{it}, C(i,t) = (j,r,s), T_i^{(1)} \geq t) = \lambda_{jrst}(M(n))\, \mathrm{P}_{jrst}(S_{it}) .$$

Since the factor $\lambda_{jrst}(M(n))$ is common to all firms in $N^T_{jrst} \cup N^C_{jrst}$, $P_{jrst}(S_{it})$ will be a balancing score for $M_i(N_{iT})$ if it is a balancing score for $T_i^{(1)}$. As shown by Lechner (2001), given the common support assumption $0 < P_{jrst}(S_{it}) < 1$.

$$\left(\varepsilon_{it}(0), \varepsilon_{it}(1)\right) \perp M_i(N_{iT}) \mid \mathrm{P}_{jrsT_i}(S_{iT_i}).$$

Note that this is a non-trivial extension of the classical matching result, as N_{it} is a counting variable, not a binary treatment indicator.

We will consider the following treatment characteristics:

$$m(k) = (T^{(k)}, A^{(k)}, S^{(k)})$$

where $A^{(k)}$ is the amount of funding, and $S^{(k)}$ the main source of funding associated with the *k'*th treatment. Because of the multidimensional character of the treatment trajectory, different types of average treatment effects among the treated (ATT) may be estimated. We will present ATT by main policy instrument (*S*), amount of support (*A*), and age group (*s*), denoted $\tau^{(S,A,s)}$:

$$\tau^{(S,A,s)} = \sum_n \Pr\left(N_{iT} \geq n \middle| S_i^{(n)} = S, A_i^{(n)} = A, Age_i^{(n)} = s\right) \tau^{(S,A,s,n)}$$

Where

$$\tau^{(S,A,s,n)} = E(\tau_i^{m_i(n)} \big| N_{iT} \geq n, S_i^{(n)} = S, A_i^{(n)} = A, Age_i^{(n)} = s)$$

and by source (*S*) and amount (*A*), denoted $\tau^{(A,S)}$:

$$\tau^{(S,s)} = \sum_{n,a} \Pr\left(N_{iT} \geq n, A_i^{(n)} = a \middle| S_i^{(n)} = S, Age_i^{(n)} = s\right) \tau^{(n,S,A,s)}$$

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