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The impact of public R&D support on firms' patenting

TALL SOM FORTELLER

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Abstract:
We examine the impact of both R&D tax credits and direct R&D subsidies on Norwegian firms' patenting. Whereas direct subsidies are aimed at projects with low private and high social return, tax credits do not discriminate between projects or technologies. We find that both direct subsidies and tax credits have significant positive effects on patenting. However, the magnitude of the effects depend critically on the firms' pre-treatment characteristics. In particular, the statistically significant estimates are all related to firms with no patent applications prior to obtaining support. Moreover, we estimate that direct subsidies have triggered at least three times as many granted patents per NOK million of support compared to tax credits. Our results suggest that R&D support should be directed to promote innovations at the extensive margin, i.e. to firms with a high potential of becoming innovative rather than to firms with a record of being innovative. Moreover, as targeted subsidies generate more innovations, society would benefit from distributing more of the subsidies to priority areas.

Keywords: Patenting, R&D policy, Treatment effects, Stratification, Matching, Poisson regression

JEL classification: C33, C52, D24, O38

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Sammendrag

I denne artikklen undersøker vi virkningen av offentlig støtte til forsknings- og utviklingsinnsats på omfanget av patentering i norske foretak. Vi analyserer både skattefradragsordningen SkatteFUNN og direkte FoU-støtte fra Norges Forskningsråd og Innovasjon Norge. Vi finner at både direkte støtte og SkatteFUNN har positive effekter på patentering. Effektens omfang er imidlertid avhengig av foretakenes egenskaper før de får støtte. De statistisk signifikante estimatene er alle relatert til foretak uten tidligere patentsøknader, dvs. før de mottar støtte. Videre anslår vi at direkte støtte har utløst minst tre ganger så mange innvilgede patenter per krone i støtte sammenlignet med SkatteFUNN. Våre resultater tyder på at FoU-støtte bør gis til foretak med stort potensiale for å innovere, snarere enn foretak som allerede har innovert – iallfall gjelder dette mht. patenterbare innovasjoner. Videre, siden vi finner at målrettede subsidier genererer flere innovasjoner enn SkatteFUNN, tyder våre resultater på at samfunnet vil dra nytte av å distribuere mer av støttene til prioriterte områder enn det som har vært tilfellet til nå.

1 Introduction

Many countries undertake policies aiming to increase research and develoment (R&D) activity, since a strict reliance on a market system may result in underinvestment in R&D and innovation activities, relative to the socially desirable level (Griliches, 1992; Martin and Scott, 2000; Hall and van Reenen, 2000). Market failures arise because of e.g. external knowledge spillovers, limited appropriability and financial constraints. In this paper we examine the impact of two different innovation policy instruments on Norwegian firms' innovation, measured by the propensity to patent. The innovation policies considered are the Norwegian R&D tax credit scheme *Skattefunn* and the two major sources of direct R&D subsidies in Norway: The Research Council of Norway and Innovation Norway.[1] Innovation policies to support private R&D activities should in principle reflect the size of the external spillovers from the research (Goulder and Schneider, 1999; Straathof et al., 2014). Even if such spillovers are found to differ between innovating firms, they are difficult to measure. The Norwegian R&D tax credit scheme is "technology neutral" in the sense that it offers the same subsidies for any type of technology or sector. On the other hand, both the Research Council and Innovation Norway offer specific programs targeted at specific industries or technologies (e.g. environmental technologies).

A common argument against direct subsidies is that the state should not try to "pick winners". In line with this view, tax incentives have become an increasingly popular policy tool over the last decades.[2] Nevertheless, Mazzucato (2013) argues that we need to shift the focus away from the worry that the state is picking winners, and towards the needs of complex, network dependent innovation sectors. When policy makers target priority technology areas as with direct subsidies, they are aware that such projects typically involve a higher risk of failure, even if the project has a high potential value. The tax credit scheme, on the other hand, does not take into account that particular technologies are exposed to greater market failures than others, e.g. environmental technologies (Acemoglu et al., 2012), public good issues (Calel and Dechezleprêtre, 2016), and possible larger knowledge externalities (Dechezleprêtre et al., 2013; Mazzucato, 2013).

[1] Innovation Norway is a government body for promoting industry development.

[2] R&D tax incentive schemes are widely adopted in advanced economies including the United States, Japan, and all EU countries except Germany and Estonia (Straathof et al., 2014).

We use Norwegian firm level registry data on patents which have been assigned to firm identification numbers, allowing us to merge data on patents with various other registry data sets, such as innovation policy databases. These data have full coverage of limited liability firms with detailed accounting and employment information. We will refer to the combined data as the Business Register. We merge the Business Register with survey data on firms' R&D-expenditures. The R&D survey data combine two sources: the annual R&D census and questionnaire data from firms that have applied for tax credits. The questionnaire data contain information about R&D expenditures each year during the three previous years.[3] Combining the two R&D surveys enables us to track the recent R&D history of about 85 percent of the firms that obtained any form of public R&D support during the observation period (see below).

We contribute to the existing literature in three ways. First, we investigate potential differences in the propensity to patent between the response of a technology neutral R&D tax credit scheme and direct R&D subsidies on innovation in general. Second, we are able to include all the major sources of R&D subsidy programs in one country in our analysis; both direct subsidies (grants) and tax credits, and to study the effects of these programs. Although there are other studies that address multiple sources of public support (e.g. Czarnitzki and Lopes-Bento, 2013 and Dumont, 2017), we are, to the best of our knowledge, the first to analyse the impact on an innovation outcome (patenting) of *all* major sources of support in one country over a relatively long period of time (2002–2013).[4] Third, according to both theoretical and empirical approaches to the economics of innovation (see Cohen, 2010, for a literature overview), specific characteristics of firms are also likely to influence innovation. Our rich data set allows us to control for observed firm heterogeneity through a wealth of control variables.

There is a large literature on the effects of public R&D support on private R&D, for example, Almus and Czarnitzki (2003) find positive effects on the R&D intensity, and both Lokshin and Mohnen (2013) and Moretti and Wilson (2014) find positive effects on R&D. Bøler et al. (2015) find that the introduction of the Norwegian R&D tax credit scheme in 2002–2003 had positive effects on R&D. However, increased R&D expenditures is not equivalent to more innovations. For instance, nominal R&D expenses might increase because firms adapt to the

[3]See Section 4.2 in Benedictow et al. (2018) for a description of this data set.

[4]In a related study, Nilsen et al. (2018) analyse the impact of public R&D support in Norway on firms' output and employment growth, labour productivity and returns on assets, but not on innovation outcomes.

policies by reclassifying spending that they otherwise would not have characterized as R&D. Tax credit schemes could be particularly vulnerable to such adaptations. Relatively few studies investigate the effect of R&D subsidies on innovation outcomes. Among them are Bronzini and Iachini (2014) and Bronzini and Piselli (2016) who both find positive effects on patenting of an R&D subsidy program in northern Italy. Dechezleprêtre et al. (2016) find that tax deductions for R&D expenses in the UK increased the propensity to patent. 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.

Earlier studies of the Norwegian tax credit scheme utilize that tax credits are capped at R&D expenditures exceeding a certain threshold (e.g. Bøler et al., 2015; Hægeland and Møen, 2007). However, the identification strategies used typically do not take into account that firms may apply for funding from multiple sources or apply many times.[5] Our approach is to use a quasi-experimental design where firms that received support (*treated firms*) are matched with a control group according to the pre-treatment characteristics of the supported firms.

We find that both direct subsidies and tax credits have significant positive effects on patenting. However, we estimate that direct subsidies have triggered almost three times as many granted patents per NOK million in support compared to tax credits. Nevertheless, the effects depend critically on the firms' pre-treatment characteristics. In particular, we find that the public policies only give incentives for more patenting among firms with no patent applications prior to obtaining support. When we control for firms' R&D experience *and* their history of patenting, we find no evidence that other variables, such as firm-size or firm-age, have a separate impact on the efficiency of the R&D-support schemes.

The rest of the paper is organized as follows: Section 2 contains a description of the data and the variables used in the empirical analysis. The econometric model is presented in Section 3 and the results in Section 4. Finally, Section 5 concludes and suggests some policy implications.

[5] A part of the identification strategy is that the tax credit scheme is assumed to lower the marginal cost of R&D only for firms with R&D expenditures below the cap prior to the introduction of the scheme (in 2002–2003). However, this assumption is less plausible when firms have access to several sources of funding as in our study, or can make intertemporal adjustments. For example, the fact that the number of *Skattefunn* projects in Norway dropped substantially just after its implementation phase (2002-2003) (see Figure 2.2. in Benedictow et al., 2018), suggests that some R&D projects may have been postponed to benefit from the introduction of the scheme, rather than having been triggered by it.

2 Data sources and description of variables

Drawing on administrative sources and survey data, we have prepared a firm-level panel data set spanning the years from 1995 to 2014, except for the data on innovation polices and the related R&D questionnaire data, which are collected from 2002, when the tax credit scheme was introduced in Norway, and onwards.

The Norwegian patent data contain unique firm identification numbers that allow for a reliable match of the patent data to the other data sets.[6] Data on innovation policies are gathered from three different sources: Innovation Norway's databases, the PROVIS database from the Research Council of Norway and the *Skattefunn* database. These data sources are used to obtain information related to R&D support for all the firms in the Business Register from 2002 and onwards.[7]

To be able to distinguish between firms with regard to the level of their R&D activity prior to the receipt of R&D support, is particularly important in order to identify causal effects of the policies. Otherwise we risk confusing the effect of doing R&D (which *cet. par.* increases the probability of obtaining R&D support) with the effect of the policy itself. Our primary source of information about firms' R&D expenditure is the Business R&D census.[8] It is mandatory for all firms that are included in the sample selected by Statistics Norway. This sample covers all firms in the business enterprise sector with at least 50 employees. Among firms with 10-49 employees, stratified random samples of about 30 percent of the population are drawn each year in the main R&D industries (2-digit NACE), with smaller shares in the other industries. Firms with 5-9 employees are also included in the census, but the coverage is much smaller for these firms. Regardless of size or industry, all firms that reported significant R&D activity in the previous survey remain included in the next one.

Firms included in the R&D census account for about 50 percent of both the total number of

[6] In most countries, there is no unique identifier allowing researchers to link intellectual property information directly to other firm-level data (Helmers et al., 2011). Instead, the names indicated on patent documents, including assignee and inventor names, and the firm names contained in firm-level databases are used to merge data sets. For example, PATSTAT and the US patent office provide identifications only by names. Even if the patent offices have harmonized the name use within their organizations, name harmonization with other data sources is challenging (Helmers et al., 2011; Tarasconi and Kang, 2015).

[7] If more than one firm participates in a project, the data from the PROVIS-database are only available for the main contractor firm.

[8] The census has been annual since 2001 and was bi-annual from 1995 to 1999.

patents in the Business Register and a similar share of total R&D support. Thus, the sole reliance on the R&D census for the classification of firms with regard to their R&D activity would mean that about half of the support had, from the outset, to be excluded from the estimation sample. Even more importantly, the sample would not be representative of the population of supported firms, as mainly medium sized and large firms are included in the census. Fortunately, we are able to supplement the R&D census with questionnaire data from the *Skattefunn* applications regarding each of the applicants' R&D expenditures three years prior to applying. These data are collected by the The Research Council of Norway and include information on R&D expenditures for most firms included in the *Skattefunn* database.

A detailed description of key variables is provided below, where they are grouped into three main categories: measures of innovation (Section 2.1), measures of innovation policies (Section 2.2), and determinants of innovation (Section 2.3).

2.1 Innovation measures

We use register data on patent applications and granted patents as measures of innovation. In contrast, innovation measures based on surveys, such as the Community Innovation Survey (CIS), may be prone to measurement errors as they depend on the respondents' own judgement and accuracy. Comparing the data from the Norwegian CIS with registered patent applications from the Norwegian Patent Office, reveals substantial discrepancies both with regard to the timing and number of patent registrations, raising serious concerns about the quality of the (self-reported) CIS data.

It is common but not uncontroversial to use patent counts as a measure of innovation (see e.g. the discussion in Bronzini and Piselli, 2016). An important argument in favour of using patent counts is that there are few examples of economically significant innovations that have not been patented (Dernis and Guellec, 2001; Dernis and Khan, 2004). Moreover, the analysis on granted patents allows us, at least partly, to take into account the quality of the innovation (e.g. novelty). A limitation of patent data is that are there are other means of protecting innovations, such as industrial designs, trademarks and copyrights.[9] Innovators may also prefer

[9] Unfortunately, register data on other intellectual property rights than patents are available only for a few years in Norway (e.g. industrial designs since 2010 and copyrights since 2013).

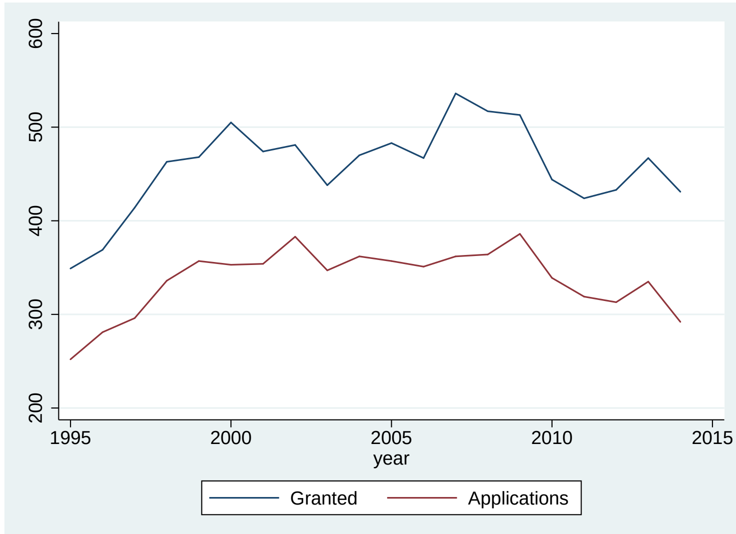

Figure 1: Yearly sum of patent applications and granted patents, by year of application.
Data source: The Norwegian Patent Office

secrecy over property rights to prevent the public disclosure of an innovation, or to save the significant fees associated with filing patents (Dechezleprêtre et al., 2011). Nevertheless, it is reasonable to assume that patent applications are strongly correlated with innovative activities and that granted patents correspond to actual innovations (see e.g. the discussion in Bronzini and Piselli, 2016). Moreover, patenting is widespread among R&D-active firms: One out of eight firms that received R&D support in Norway during 2002-2013 have applied for patents, receiving about a third of total R&D support (see Section 2.4).

We see from Figure 1 that the number of patent applications and granted patents increase until 2007–2008, but with a downward trend thereafter. Part of this drop is likely due to the financial crisis, but the number of patent applications and granted patents were still well below their pre-crisis level in 2014. We also see that the annual numbers of granted patents (by year of application) are roughly proportional to the number of applications.[10]

[10]Using data on granted patents involves potential timeliness problems because of the processing time of applications. However, to classify a patent application as *granted* we use processing data from the Norwegian Patent Office as of January 2019, allowing for a four year lag from the latest time of application in the estimation sample (December 2014) to the classification (January 2019).

2.2 Innovation policy instruments

The Norwegian innovation policy instruments can be grouped into two main categories: i) tax credits, which are rights-based subsidies, given that some formal requirements are fulfilled by the applicant; and ii) direct subsidies. Direct subsidies aim to reflect the size of the external spillovers from the research activities. The primary difference between these two innovation policy instruments is that the former typically allows firms to choose projects, whereas the latter is usually accompanied by a government directed project choice (David et al., 2000). As a result, direct subsidies involve competition between projects and firms for government funding. The two types of support are thus exposed to different types of selection biases. On the government side there are several small agencies and two large ones: The Research Council of Norway and Innovation Norway. This study only considers these two as the other agents are unimportant in comparison (see Cappelen et al., 2016).

Traditionally, Norwegian R&D support have mainly been given as direct subsidies to firms (Hægeland and Møen, 2007). The Research Council and Innovation Norway provide different types of direct subsidies.[11] The Research Council offers strategic and targeted subsidies for research where at least 50 percent of the project is expected to be financed by the firm itself.[12] The Research Council also operates larger programs designed to build long-term knowledge to encourage innovation, enhance value creation, as well as help find solutions to important challenges facing society. Innovation Norway offers direct subsidies in the form of direct grants, high-risk loans and guaranties. Both the Research Council[13] and Innovation Norway[14] offer direct subsidies for priority thematic and technology areas, such as e.g. environmental technologies.

The R&D tax credit scheme *Skattefunn* (SKF) was introduced in January 2002 to SMEs[15] but extended to all firms in the following year. It was believed that an R&D tax credit scheme

[11] The Research Council and Innovation Norway not only provide support intended to enhance innovation. The policy assignments from the government to Innovation Norway can be specified in three separate categories: In addition to innovation, Innovation Norway supports regional development and offer financial lending intended to improve survival probabilities. We exclude support intended for the two latter objectives from our data in order to identify the effects from subsidies aimed at innovation. In addition to innovation subsidies, the Research Council provides support for e.g. project establishments and knowledge-building projects not directly related to innovation, which we exclude from our data.

[12] Direct subsidies from Innovation Norway typically covers a larger percentage of the project cost. See the home page of Innovation Norway (in Norwegian) for more details.

[13] http://www.forskningsradet.no/en/Research_areas/1252498540762

[14] http://www.innovasjonnorge.no/no/finansiering/miljoteknologi/

[15] Firms with a) less than 250 employees, and b) a yearly sales income not exceeding 50 million Euros or a yearly profit not exceeding 43 million Euros (§16-40-5 Regulations for Law of Taxation)

would provide more stable conditions for the business community than direct grants (see Cappelen et al., 2010). Firms are entitled to tax credits as long as the R&D project has been approved by the *Skattefunn* division of the Research Council. The SKF scheme grants large firms 18 percent and SMEs 20 percent of approved R&D expenses up to a cap. The cap was NOK 4 million until 2008 and NOK 5.5 million from 2009-2013. Thus, the maximum tax refund for a large firm in 2013 was about NOK 1 million (about EUR 110,000).[16]

Although low access to loans or private venture capital can hinder innovation, it is in practice difficult to identify firms that truly are exposed to such constraints. A common conception is that innovation and economic growth is created by "entrepreneurial" small or medium sized firms (SMEs). However, there is little empirical evidence to support this assertion. As Mazzucato (2013) points out, the relationship between firm size and innovation is sensitive to various factors such as industry or technology specific effects. Moreover, many small firms tend to be young.

Based on the current design, the purpose of tax credits is not to reflect the size of the external spillovers from the research. Unlike direct subsidies, the Norwegian tax credit scheme does not discriminate between types of R&D projects or technologies. It is thus unlikely that tax credits contribute in reducing the market failures and challenges that face the development of particular types of technologies, as for example environmental technologies (Acemoglu et al., 2012; Dechezleprêtre et al., 2013; Calel and Dechezleprêtre, 2016). Even if tax credits may make marginal projects profitable, the firms may still focus on projects with the greatest short term returns.[17] Tax credits may therefore not promote new technologies that are not close to the existing market solutions (David et al., 2000).

An important difference between direct subsidies and tax credits, is that tax credits are obtained by many more firms, but in much smaller amounts per firm. For example, more than 60 percent of tax credits (SKF) are given in amounts of less than NOK 500,000 per firm-year. The corresponding numbers for Innovation Norway (IN) and the Research Council (RCN) are

[16] The tax refund takes place at the end of the year when the actual R&D expenses were incurred. If the firm's taxes are less than the refund, the remaining tax credit is given as a direct grant. See Benedictow et al. (2018) for more details abut the scheme.

[17] Assume that a firm has two potential projects, A and B, and apply for public funding of the "best" project, say A. Furthermore, assume that it carries out both A and B if it gets funding and only A if not. Thus, even if A is the supported project, B is the marginal project and the "impact" of the support is that B is carried out .

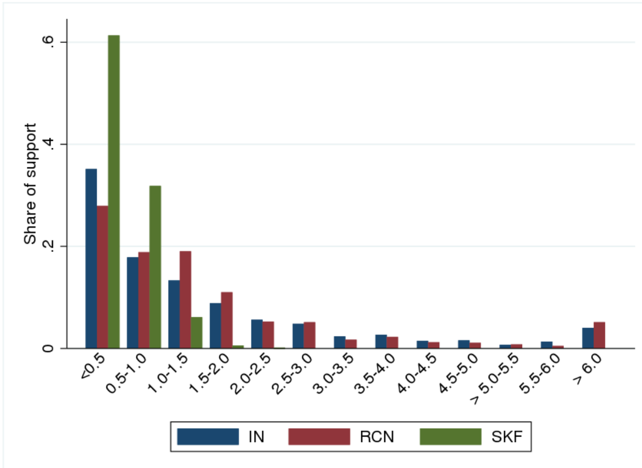

FIGURE 2: Distribution of support in NOK mil. from each policy instrument at the firm-year level

35 and 30 percent. On the other hand, a significant share of IN and RCN grants exceed NOK 6 million per year. This is illustrated in Figure 2.

Table 1 provides descriptive statistics of the shares of received R&D support and filed patent applications by (broad) industry classification, firm size (small, medium and large) and region. We see that support is highly concentrated in a few industries, with about a third of total support going to Professional, technical and scientific services (22 percent of tax credits and 41 percent of direct subsidies). Next comes Information and communication (with 25 percent of tax credits and 12 percent of direct subsidies) and Manufacturing of Machinery and electronics (14 percent of tax credits and 16 percent of direct subsidies). These three industries receive 65 percent of total support, but account for only 16 percent of the *firm-years* (a firm observed for one year). In contrast, Other services account for 75 percent of the firm-years, but only 14 percent of total support. Patenting is highly concentrated in two industries: Professional, technical and scientific services (34 percent) and Manufacturing of machinery and electronics (27 percent). In comparison, Other services and other Manufacturing (excluding machinery and electronics), account for 16 and 12.5 percent of the patent applications.

TABLE 1 HERE

Large firms ($\geq$ 250 employees) make up less than 0.5 percent of the firm-years in the

Business Register, receive 4 percent of the tax credits, 13 percent of the direct subsidies and hold 24 percent of the patent applications. Large firms thus patent more relative to the funding they receive and – much more – relative to their numbers.[18]

Figure 3 depicts the share of *treatment-years*, defined as firm-years with tax credits or direct subsidies, relative to all firm-years in the given industry (upper chart) or in the given employment category (lower chart). The industries with the highest share of treatment-years relative to firm-years are Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of machinery and electronics; Manufacturing of textiles and food; and Information and communication. There is a strictly increasing relation between number of employees and the receipt of R&D support (lower chart). Direct subsidies are disproportionally given to large firms: Large firms have more than 10 percent probability of receiving direct subsidies and 8 percent probability of receiving tax credits in a given year, compared to 5 percent and 1 percent, respectively, for firms with 10–49 employees.

2.3 Determinants of innovation

A number of firm characteristics may be important drivers of innovation – in addition to public policies (see Klemetsen et al., 2018, for a systematic discussion). This is illustrated in Figure 4. The upper panel depicts the average number of patent applications vs. granted patents per firm-year in each of the industries. Figure 4 also depicts the number of patents per firm-year by number of employees (lower panel). The upper panel reveals large differences between industries with regard to the propensity to patent. The three top industries in this respect are Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of machinery and electronics; and Mining, oil and gas extraction. Then comes Manufacturing of metals and minerals and Professional, scientific and technical activities. Other industries have an almost negligible number of patents per firm-year.

From the lower chart in Figure 4, there appears to be an exponential relation between firm size and the propensity to patent. The number of patent applications per firm-year is 0.25 among

[18]The different regions in Norway account for a similar share of R&D support as of firm-years. The exception is Middle Norway, which gets a disproportional share of directs subsidies (18 percent) compared to firm-years (8 percent). This is due to firms in the industry Research and Development (NACE 72), of which many participate in research networks with the Norwegian Technical University located mainly in the city of Trondheim.

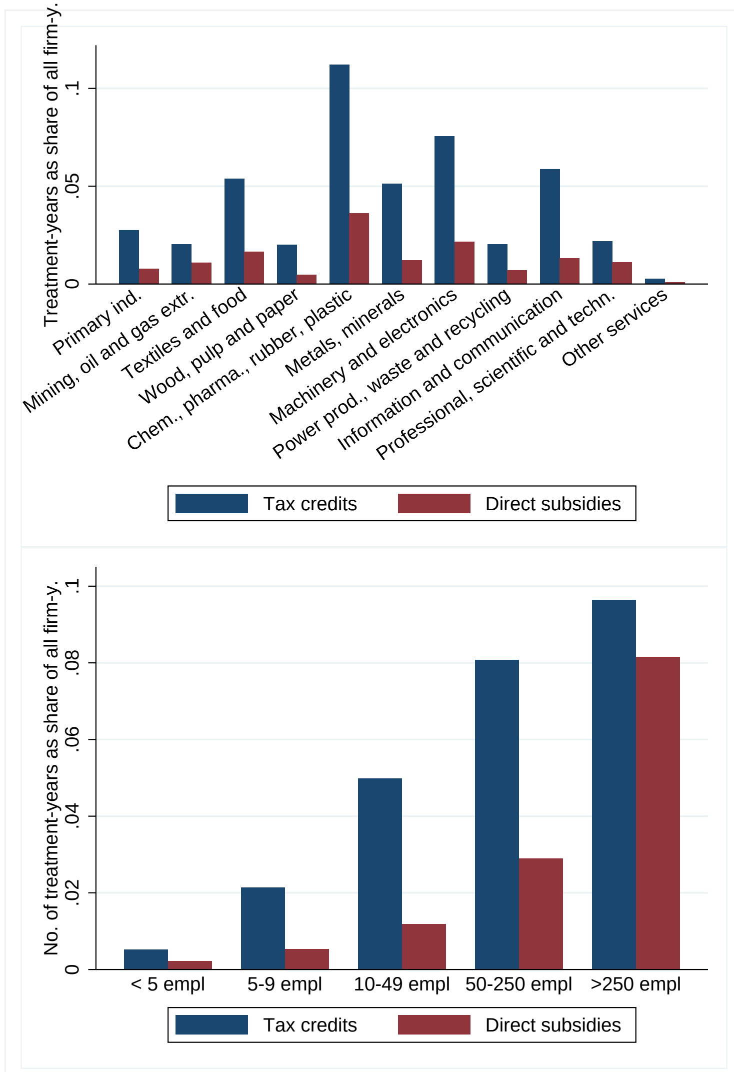

FIGURE 3: Treatment-years according to source of funding (tax credits vs. direct subsidies) as share of all firm-years, by industry (upper chart) and number of employees

large firms, compared to only 0.03 among medium sized firms, and less than 0.01 among small firms.

By taking into account both observed heterogeneity (control variables) and unobserved heterogeneity (represented by fixed or random effects), we aim to eliminate the problem of omitted variable bias when analyzing the effects of public R&D support. We will control for R&D-activity, patenting history, firm size, age, industry and region. Some of these variables are clearly endogenous and therefore would be "bad controls" in a regression model. Instead, we apply a quasi-experimental design. That is, we mimic – through a stratification-based matching procedure – the conditions of a randomized experiment as closely as possible by using the pre-treatment values of the variables. The approach will be detailed in Section 3. The critical prerequisite for our analyses is that our control group of firms is representative of the non-treated (counterfactual) outcomes for the firms that receive support, i.e. the outcomes that would have been realized if they had not received support.

2.4 Sample size and summary statistics before matching

Table 2 shows summary statistics for the Business Register, separating between "All firms" and "Patenting firms". The upper part of the table shows that, in general, patenting firms are much larger, more capital intensive and have higher labour productivity than non-patenting firms. They are also somewhat older, with a mean firm-age of 12.5 vs. 10.5 years, but *not* more profitable: the mean (median) return on assets is 2.1 (3.0) percent vs. 6.0 (4.1) percent for patenting vs. all firms. The most striking difference is perhaps that among patenting firms, over 50 percent obtained R&D support, compared to just 3.7 percent among all firms.

Column 1 in the lower part of Table 2 shows that the Business Register consists of 335,763 firms, of which only 2,024 have at least one patent application during 2002-2013 (Column 3). The number of treated firms, i.e. firms receiving R&D support, is 8,834. They received in total NOK 21.9 bil. in R&D support between 2002 and 2013. Of the treated firms, 1,081 (i.e. 1 out of 8) are patenting firms, receiving more than a third of the total R&D support in the Business Register. Thus, R&D support is given highly disproportionate to patenting firms.

TABLE 2 HERE

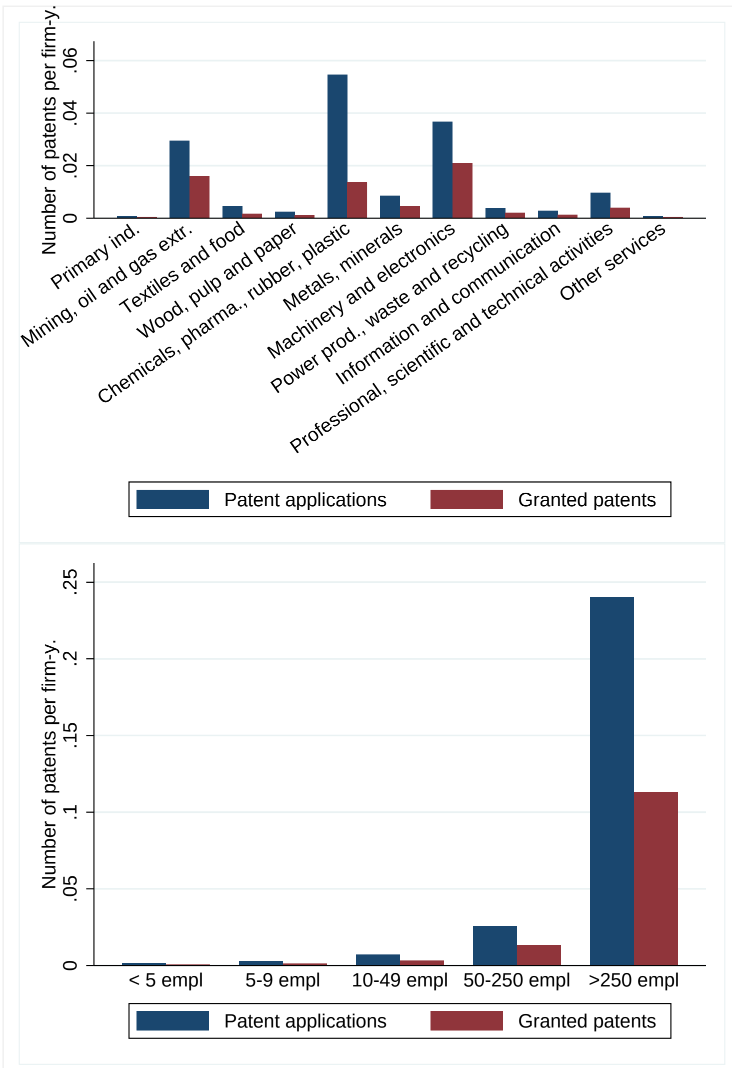

FIGURE 4: Average number of patent application and granted patents per firm-year, by industry (upper chart) and number of employees

Table 3 contains descriptive statistics for treated firms after the merger of the Business Register with our two sources of R&D survey data. Comparing Column 1 and 2 in the upper part of Table 3, we see that the need to classify firms as either R&D-active or R&D-inactive at the time of treatment assignment reduces the sample size by less than 15 percent. The number of treatment-years is reduced from 27,224 to 23,737 and the amount of R&D support from NOK 21.9 bil. to NOK 19.1 bil.

In the lower part of Table 3 (Column 3), we see that about 70 percent of treated firms were R&D-active before receiving treatment. Perhaps even more strikingly, R&D support is given disproportionate to young firms. The lower part of Table 3 (Column 1) shows that 43 percent of the treated firms were 3 years or younger when first assigned to treatment. In comparison, 30 percent of *all* firm-years in the Business Register are related to firms aged 3 years or less (see upper part of Table 2). These figures reflect that the R&D support schemes are generally more popular among start-up than incumbent firms, but also that IN and RCN have programs that target young firms.[19]

The shares of patenting firms before and after the merging of the Business Register with the two sources of R&D survey data are almost identical: 11 and 12 percent (Column 1 and 3 in the lower part of Table 3). Moreover, comparing Column 1 (Column 2) with Column 3 (Column 4), respectively, we see that the mean (median) number of employees among the treated firms is 32.1 (5.0) in the Business Register vs. 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) firm-age is 8.6 (5.0) vs. 9.0 (5.0), the mean (median) return on assets (RoA) is 1.0 (2.0) percent vs. 2.0 (3.0) percent, and the mean (median) level of labour productivity is 0.45 (0.40) vs. 0.46 (0.41).

TABLE 3 HERE

2.5 The matched estimation sample

Our matching is based on stratification: treated firms are matched with non-treated firms belonging to the same stratum at the time of matching. The matching (stratification) variables (X) are: NACE industry (at the 2-digit level), region, firm-age, employment, R&D expenditure

[19] An example is "Etablererstøtte" (*start-up support*) from IN.

and (lags of) number of patent applications. The matching variables should affect both the dependent variable and the probability of treatment. That this is the case with regard to X is evident from the discussions and the descriptive statistics presented above. We divide the possible outcomes of the matching vector X into strata, x, as follows:

$$x = (ind, reg, age, empl, rd, pat)$$

where *ind* is a 2-digit NACE industry, *reg* denotes a region (see Table 1), *age* is an age interval (0–3, 4–9, or >9 years), *empl* is an employment interval (<5, 5-19, 20-49, 50-249, ≥250 employees), and *rd* is *R&D-status*: a dummy for whether the firm had positive R&D expenditures (including R&D support) during the three preceding years *not* including the current one. Finally, *pat* is a dummy for whether the firm has had at least one patent application since 1995.

The final estimation sample is a combination of sampling from the R&D census and the Business Register, as treated R&D-active firms (firms with positive R&D expenditure) are matched with non-treated R&D-active firms according to the R&D census. On the other hand, R&D-inactive firms (according to R&D expenditure reported in the R&D census *or* in the supplementary R&D questionnaire) are matched with firms from the Business Register with no recorded R&D activity.

Table 4 shows that the final matched sample consists of 13,528 (3,406+10,122) treatment-years, comprising NOK 11 bil. in total R&D support, of which 70 percent was received by firms that were R&D-active at the time of treatment assignment. Moreover, 4.5 (2.6) percent of the R&D-active (R&D-inactive) firms were classified as patenting firms prior to treatment. The total number of patents by firms included in the estimation sample is 3,148. Of these, 2,441 (328+2,113) are related to treated firms.

TABLE 4 HERE

The effect of the matching is a substantial reduction of the estimation sample: the final estimation sample described in Table 4 comprises 3,622 (1,134+2,528) treated firms, compared to 6,838 treated firms with R&D information in the Business Register (Table 3). This reduction in sample size is the price we pay for a matched estimation sample with excellent balancing properties. First, by construction, the matching is *exact* with regard to the categorical variables

R&D-activity (rd), prior patenting (pat), industry (ind) and region (reg). Second, from the upper part of Table 4, we see that the matched estimation sample is almost perfectly balanced with regard to the mean of employment and firm-age. That is, we do not reject that the means are equal for the treated and controls (this is easily derived from the reported standard errors (SE) in Table 4).[20] Third, we observe good balancing properties in Table 4 also with regard to variables *not* used in the stratification, such as labour productivity, capital intensity and return to assets. The explanation is that neither of these variables are significant predictors of treatment *conditional* on the matching variables. In contrast, the matching variables are highly significant predictors of treatment.[21]

3 Empirical model

As already stated, our main research question is whether the two main types of innovation policies – tax credits and direct subsidies – spur innovations in the form of patenting. However, a firm receiving a large amount of support can have a higher propensity for patenting *cet. par.* We will control for this selection problem by means of statistical matching, as discussed above. Furthermore, we will allow for heterogeneity in treatment effects across firms and programs. In this way, we can relate the estimated effects to the characteristics of firms and policies, such as the amount and source of support, when interpreting the results (see Section 4).

To take into account that R&D support tend to take the form of annual payments and/or tax deductions in *consecutive* years, reflecting the duration of the supported projects, we define a *treatment* as a sequence of consecutive firm-years with support. We will refer to the first year in the sequence as the year of *treatment assignment*, denoted T_i (the firm receives support in T_i but not in $T_i - 1$). The number of consecutive years with support is denoted D_i (the firm receives support in $T_i, T_i + 1, ..., T_i + D_i - 1$, but not in $T_i + D_i$). In the case of non-consecutive years with support, we will consider this as repeated treatments, with a separate matching for

[20] When the reported mean values are used with the standard errors to calculate 95 percent (pairwise) confidence intervals for treated and controls, it is easily seen that they overlap. Formal tests of equality of both means and medians are available from the authors upon request. In all cases these tests lead to a clear non-rejection.

[21] Comparing Table 1 (before matching) and Table A.1 in the Appendix (after matching), give further evidence that the matched estimation sample is representative for the population of treated firms as a whole, including the industry and regional distributions. Thus, while the matching substantially reduces the sample of treated firms that can be analysed, the matched sample is not skewed with regard to any dimension of x, such as e.g. firm size or firm age.

each treatment (see below, especially Footnote 24).

To identify separate effects of treatments funded by different policy instruments, we must take into account that co-funding is widespread. For this purpose, we define the *main policy instrument* as the source of the largest amount of support at the treatment level by summing the NOK support from all sources over the treatment period. Although research projects may receive public funding from several sources, there tends to be one dominant source of funding (we will address the robustness of our results to the definition of the policy instrument in Section 4.3).

In our empirical model, the dependent variable, P_{it}, is a count variable denoting either the number of granted patents or patent applications of firm i in year t. Let $P_{it}(d)$ denote the outcome of the dependent variable as a function of treatment status, where $d = 0$ means non-treatment and $d \in \{1, 2, ...\}$ means treatment with duration d (d consecutive years of support). Note the important difference between $\mathrm{P}_{it}(D_i)$ and $\mathrm{P}_{it}(d)$: $\mathrm{P}_{it}(D_i)$ is the *realized* outcome, while $P_{it}(d)$, for $d \in \{0, 1, 2, ...\}$, are the *potential* outcomes. In particular, we will refer to $P_{it}(0)$ as the *non-treated* outcome.

Let $S(X) = x$ be the mapping that maps the matching vector X into a unique stratum x, as explained in Section 2.5. We assume that, conditional on x, the causal effect of the treatment is represented by a fixed or random effect, τ_i . That is, the conditional mean of the potential outcome $P_{it}(d)$ is given by:

$$\begin{aligned} E(P_{it}(d)|S(X_{iT_i}) = x, \tau_i, D_i) = & \quad exp(\tau_i 1(1 \leq s \leq d)) \\ \times & \quad E(P_{it}(0)|S(X_{iT_i}) = x) \end{aligned} \tag{1}$$

where $s \geq 0$ is the number of years since treatment assignment (T_i), $t = T_i + s$ and $1(A)$ is the indicator function which is one if the statement A is true and zero otherwise. The key identifying assumption in Equation (1), is that the stratification $S(X)$ is sufficiently rich so that conditional mean independence (CMI) holds with regard to the non-treated outcome. That is:

$$E(P_{it}(0)|S(X_{iT_i}) = x, \tau_i,\ D_i) = E(P_{it}(0)|S(X_{iTi}) = x) \text{ for } t \geq T_i \tag{2}$$

The specification consisting of Equations (1)-(2) is a multiplicative version of the (linear) matched Diff-in-diff model advocated by e.g. Blundell and Costa Dias (2009), where treatment-specific effects (τ_i) are also considered as fixed or random. As in the linear model, CMI means that whatever treatment, D_i, the firm is assigned to at T_i, this assignment is per se uninformative about the expected non-treated outcome of the dependent variable (given x).

3.1 Common trend

The expected non-treated outcome is assumed to be determined by a *common trend* – denoted $m_t(x, T_i)$ – depending on what stratum, x, the firm belongs to at the time of treatment assignment, T_i:

$$E(P_{it}(0)|S(X_{iT_i}) = x) = exp(m_t(x, T_i)) \tag{3}$$

Importantly, $m_t(x, T_i)$ only depends on predetermined values and therefore is not affected by the treatment.

If we were to estimate the above model on a given reference population, e.g. as a count data regression model with $P_{it}(D_i)$ as the dependent variable, the causal effects would be identified solely by the functional form of $m_t(\cdot)$. Since D_i and X_{iT_i}, by assumption, are highly correlated, any error in the specification of the common trend could turn up as a spurious "treatment effect". Moreover, for non-treated firms ($D_i = 0$), T_i is not well-defined: it is a *potential* year of treatment assignment.

To address these issues, we combine stratification and statistical matching as follows. First, we define the cell $C(x, T)$ as the set of all firms observed to belong to the strata x at T. The subset of firms in this cell that are assigned to treatment at T (i.e. firms with $T_i = T$) is denoted $N^T(x)$.[22] The corresponding control group, $M^T(x)$, is a subset of non-treated firms in $C(x, T)$.[23] The main identifying restriction with regard to the estimation is that the firms in the control group, $M^T(x)$, have the same common trend, $m_t(x, T)$, as the firms in the treatment group,

[22] Formally $N^T(x) = \{i : S(X_{iT}) = x, T_i = T, D_i > 0\}$ and $C(x, T) = \{i : S(X_{iT}) = x\}$

[23] In principle, any non-treated firm in $C(x, T)$ could be in the control group. Some details are in order here: First, all firms in the cell that are assigned to treatment at T will have the same control group (many-to-many matching). Second, any non-treated firm could potentially belong to several control groups (one for each T). To achieve uniqueness *and* efficiency, a firm is assigned to a (unique) control group according to a simple rule which attempts to balance the ratio of number of treated to controls across the cells. Third, we do not exclude firms from potentially being in a control group until they get treatment (if any), since such exclusions would depend on future outcomes of endogenous variables (e.g. future R&D) and thus violate CMI.

$N^T(x)$.

3.2 Treatment response function

Since pinpointing the timing of the effects from the policies are challenging and little guidance is available from the literature, we model the effect of the treatment as simple as possible: A treatment assigned at T_i induces – with a one-year lag – a proportional shift in the expected number of patents equal to $\exp(\tau_i)$ during the treatment. Of course, different lag choices can easily be accommodated. In the empirical section we will also investigate "long term" or "post-treatment" effects.

As we cannot estimate a separate parameter τ_i for each treatment, further assumptions must be made. Moreover, to identify separate effects of the different policy instruments, we must take into account the source of funding. Our approach is to relate τ_i to observed variables, both with respect to firm characteristics (x) and the source of funding.

Formally, let the dummy variables TC_i and DS_i be one if the main policy instrument is, respectively, tax credits and direct subsidies. Furthermore, let $P_i = (TC_i, DS_i)$ and assume:

$$\begin{aligned} E(\exp(\tau_i)|S(X_{iT}) = x, D_i, P_i\,) &= \exp(\pi(x)TC + \gamma(x)DS_i) \\ &\equiv exp(\tau(x, P_i)) \end{aligned} \tag{4}$$

We will henceforth refer to $\tau(x, P_i)$ as the treatment response function. The treatment response function expresses the *relative* increase in the expected number of patent applications from the policy P_i: $\tau(x, P_i)$ is equal to $\pi(x)$ or $\gamma(x)$ – depending on whether $TC_i = 1$ or $DS_i = 1$. Although the treatment response, in principle, is allowed to depend on firm characteristics (x) in a non-restricted way, we mostly focus on the impact of pre-treatment R&D-status (rd) and patenting (pat) in our empirical analyses (see Section 4). The potential impact of firm-size and firm-age will also be investigated. Moreover, we will examine the impact of policy mixtures, i.e. co-funding of the same treatment from multiple funding agencies.

3.3 Estimation

$P_{it} = P_{it}(D_i)$ is the dependent variable. To estimate the treatment response function, $\tau(x, p)$, we utilize that in the matched sample the following holds:[24]

$$\begin{aligned} &E(P_{it}|S(X_{iT}) = x, D_i, P_i) = \exp(\tau(x, P_i)1(1 \leq s \leq D_i) + m_t(x, T)) \quad && i \in N^T(x) \\ &E(P_{jt}|S(X_{jT}) = x) = \exp(m_t(x, T)) && j \in M^T(x) \end{aligned} \tag{5}$$

where $s \geq 0$ is the number of years since the start of treatment and $t = T + s$. The notation $m_t(x, T)$ underscores that the common trend is specific to the cell, i.e. it is non-parametrically identified as *cell-specific* time-effects. Hence, we specify $m_t(x, T)$ as *a fixed* year-effect (specific to t) plus a cell-specific *random* year-effect (specific to (t, x)). The assumption of random cell-specific year-effects is justified since X_{iT} and D_i are independent in the matched sample.[25]

In view of the discussion in Section 2, a key assumption is that $m_t(x, T)$ does not depend on variables that may be affected by the treatment, such as contemporaneous R&D activity or employment. Current endogenous variables are "bad controls". Therefore, the control variables are used only for stratification (matching), but not included as explanatory variables in the regressions.[26]

It is not possible to identify causal effects in this model if fixed firm effects are also included. The reason is that the firm is observed from the start of treatment ($s = 0$) until the end of treatment ($s = D_i$) – or possibly a few years more. An implication is that a fixed firm-dummy will be (almost) perfectly correlated with the treatment indicator $1(1 \leq s \leq D_i)$. Our identifying assumption is that the firms in the control group represent the non-treated outcomes of the treated firm, not – as in a fixed effects model – that the treated firms patent more just after (or

[24] A firm (i) that obtained treatment at $T_i = T$ is 1) considered as a treated firm from T and onwards (but not earlier); 2) it remains in the sample *after* treatment until it exits; 3) if a firm receives repeated treatments (non-consequtive firm-years with support), each new treatment is accompanied by a separate matching; 4) if an R&D-inactive firm obtains R&D support a second time, it will change status from R&D-inactive to R&D-active for the second matching.

[25] Even if the stratification may achieve independence of X_{iT} and D_i within each cell (T is the year of matching), this does not guarantee a balanced distribution of X_{iT} in the matched estimation sample. The reason is that the ratio of treated to controls varies across the cells. Based on the theory of unequal probability sampling (see Särndal et al., 1992), we correct this imbalance by means of weights, w_i, where $w_i = 1$ if $i \in N^T(x)$ (treated) and $w_j = M(\#N^T(x))/(N\#M^T(x))$ if $j \in M^T(x)$ (controls), where $\#A$ denotes number of elements in the set A, and N and M denote the total number of treated and controls across all the cells in the matched sample. Then $\sum_{j \in M^T(x)} w_j/\#N^T(x) = M/N$, i.e. the number of weighted controls per treated firm is equal to M/N in each cell. As a result, a balanced distribution of X_{iT} is achieved in the weighted matched sample.

[26] Our approach is in line with Lechner (2010) and Lechner and Wunsch (2013). Like us, they do not include control variables in the regression (Diff-in-diff) part of the estimation, only in the matching part.

during) treatment than it did before treatment.

We estimate our model using the mixed Poisson quasi-maximum likelihood estimator, i.e. with both fixed and random coefficients.[27] If the expected number of patents is correctly specified, this estimator yields a consistent quasi-maximum likelihood estimator of $\tau(x,p)$ even if the assumption of a Poisson-distribution does not hold (see Gourieroux and Monfort, 1995, Ch. 8.4).[28] Robust estimates of the covariance matrix of the quasi-maximum likelihood estimator are easily available (see Cameron and Trivedi, 2015). We will also estimate a fixed effects Poisson model as a benchmark in Section 4.

4 Results

The estimates of the parameters in Equations (4)-(5) are presented in Table 5 for patent applications and Table 6 for granted patents. The corresponding estimates of marginal effects (ME) are presented in Table 7. We report estimates along two dimensions with regard to firm characteristics (x): (1) R&D-active vs. R&D-inactive firms (rd) and (2) patenting vs. non-patenting firms (pat), where both variables are measured at the year of treatment assignment (the year of matching). Other dimensions of x (firm-size and firm-age) will be considered in Table 8.

4.1 Estimates of the treatment response function (relative effects)

Table 5 contains the results of the relative effects of innovation policies on the number of patent applications, i.e. the estimates of the treatment response function. The main policy instrument is indicated in the first column of the tables, while the second and third columns classify the treated firm according to the pre-treatment value of (rd, pat). In addition to the matching estimator explained in Section 3, we report estimates of a fixed effects benchmark model (FE). The FE model includes fixed firm-effects and calendar-year dummies in addition to the treatment variables.

TABLE 5 HERE

[27] We use the STATA command *mepoisson* with weights, where the fixed part includes the calendar year dummies, the weights w_i are defined in Footnote 25, and the mixing (random coefficients) is with regard to the cell-specific year-effects.

[28] This is not the case with the popular Negative binomial distribution unless unwarranted restrictions are placed on the overdispersion parameter (see Guimaraes, 2008; and Cameron and Trivedi, 2015)

The fixed effects (FE) specification captures correlation between unobserved firm specific effects and the treatment variables (the right-hand side variables). This feature of the model comes at the cost of throwing out from the analysis firms without patents, as time-invariant variables are automatically dropped from the FE model.[29] As a result, the FE model is more appropriate for investigating the intensity of innovation (*intensive margin*) rather than the propensity to innovate (*extensive margin*). Nevertheless, we cannot consider the FE estimates as representing causal effects. The reason is that the identification of causal effects in the FE model depends on the implausible assumption that selection into treatment is time-invariant at the firm level.

From the lower part of Table 5 we see that the number of treated firms and patent applications included in the FE estimation are, respectively, 664 and 3,193. The corresponding numbers for the matching estimator are 3,362 and 2,724. Thus, the sample for the matching estimator is much larger with respect to number of treated firms, and moderately smaller with regard to the number of patent applications.

From the results of the matching estimator in Table 5, it appears that both tax credits and direct subsidies have significant positive effects on the prevalence of patent applications. However, the effects seem to be highly dependent on the pre-treatment classification of the firm. All the significant results refer to the *extensive margin*; firms with no patent applications prior to treatment. Furthermore, it is noticeable that that the magnitude of the estimates are higher in the case of R&D-inactive firms compared to R&D-active firms. We also see that the estimates for direct subsidies are significantly higher than for tax credits.

Comparing the estimates from the matched sample and the FE model in Table 5, we see that the same parameters are significant in both models. As explained in Section 3.2, these parameters can be interpreted in terms of relative effects, i.e. relative to the non-treated outcome. However, since the expected number of patents is likely to be much higher in the FE sample because it only includes patenting firms, the magnitude of the effects are not comparable across the two models. We will return to the more interesting Average Marginal (level) Effect (AME) estimates in Table 7, i.e. the effects of the treatment on the *number* of patents.

We replicate the results of Table 5 using granted patents instead of applications in Table

[29] To retain a sample which is as large as possible, we estimate the FE model over the extended time period 1995-2014.

6. Further evidence of our main findings from Table 5 are given in Table 6. All the parameter estimates are strikingly similar in the two tables. Moreover, the significant results are related to the extensive margins and are much stronger for direct subsidies than for tax credits.

TABLE 6 HERE

4.2 Average Marginal Effect (AME)

The marginal effect of the treatment is defined as the change in the expected *number* of patents, given the pre-treatment classification of the firm (x) and the main policy instrument (P). The estimated average marginal effects (AMEs) for patent applications and granted patents are reported in the upper part of Table 7. They are derived from the corresponding parameter estimates from the matching estimator reported in Table 5 and 6.

The level of significance reported in Table 5 (for patent applications) and Table 6 (for granted patents) are translated into very similar levels of significance in Table 7. There are no significant estimates of AMEs at the intensive margin, whereas *all* estimated AMEs at the extensive margin (firms with no patent applications prior to treatment) are significant at the 1 or 5 percent level. These main findings of Table 7 hold with regard to patent applications as well as granted patents.

Some other notable results from the upper part of Table 7 are the following: 1) The expected number of patent applications or granted patents per year (μ) is close to the estimated AMEs in the case of firms without prior patenting, indicating that their *non-treated* probability of patenting is close to zero. 2) The estimated AMEs for granted patents are equal to, or slightly below, those for patent applications, but not significantly different. 3) The AME estimates in Table 7 for R&D-inactive firms (prior to treatment) are much higher for direct subsidies (in the range 0.13–0.15) compared to tax credits (about 0.01). 4) In the case of R&D-inactive firms, the estimated AMEs for direct subsidies are much higher than for tax credits also relative to the amount of support received. For example, while the mean (median) support intensity (support per year during treatment) is three (two) times higher for direct subsidies than for tax credits (see the lower part of Table 7), the estimated AMEs are higher by a factor exceeding 10.

In the the lower part of Table 7, we present estimates of sums of marginal effects (Sum

ME), defined as the sum of all the AMEs across all treatment-years. We can interpret Sum ME as the total number of patents triggered by tax credits or direct grants occurring in the data period. Regarding patent applications, the estimated Sum ME for direct subsidies and tax credits are 239 and 139, respectively. The corresponding estimates are 157 and 56 for granted patents. As seen from the lower part of Table 4, the amount of direct subsides and tax credits in the estimation sample are equal: $2.1 + 3.4 = 5.5$ (direct subsidies) and $1.2 + 4.3 = 5.5$ (tax credits). We conclude that direct subsides have been much more effective in triggering innovations as measured by patent applications and granted patents than tax credits.

TABLE 7 HERE

While previous patenting and R&D activity are clearly the most important predictors of future patenting, the treatment response function may depend on other pre-treatment characteristics (x). In particular, the descriptive statistics reported in Section 2 indicate that firm-size is a key determinant of patenting (cf. Figure 4). Moreover, we have seen that a disproportionate share (43 percent) of treated firms are 3 years or younger when first assigned to treatment (cf. Table 3). Hence, it is potentially interesting to separate between start-up firms (≤ 3 years) and incumbent firms (> 3 years) when reporting AME estimates.

In Table 8, the estimated AMEs are allowed to depend on an additional dimension *Firm Type*. In the upper part of Table 8, Firm Type refers to start-up or incumbent firm.

TABLE 8 HERE

From the results in the upper part of Table 8 (both granted and applications), we see that – conditional on (pat, rd) – the estimated AME are very similar for start-ups and incumbent firms. Not only are the estimates of the same magnitude and have overlapping confidence intervals, but in each case where the AME estimate is significant in Table 7, the corresponding pair of AME estimates in Table 8 (one for each Firm Type) are also significant.

The lower part of Table 8 displays estimated AME when Firm Type refers to firm-size (large firms vs. SMEs) – instead of firm-age. As in Table 1, a large firm is defined as having 250 or more employees. There are three main takings from the lower part of Table 8. First, among the R&D-inactive firms, there are too few large firms to even estimate AMEs. Second, among the

R&D-active firms with no prior patenting, the estimated AMEs are significant only for SMEs. Nevertheless, the estimates are almost identical for SMEs and large firms. Finally, there is weak evidence (significant at the 10 percent level) that large R&D-active firms with prior patenting have a positive AME from direct subsidies (but not from tax credits).

4.3 Robustness issues: Long-term effects and support mixture

To examine long-term effects, Table 9 presents AME estimates for the post-treatment period, defined as the period from $T_i + D_i$ +1 (two years after the end of the treatment; see Section 3) until $T_i + 2D_i$. For comparability with Table 7 and 8, the post-treatment period is defined as having the same duration ($= D_i$) as the treatment period.[30]

TABLE 9 HERE

PTAME in Table 9 expresses the average marginal effect of treatment during the post-treatment period. Similar to AME, it represents an average effect *per year* during this period. None of the estimates in Table 9 are even close to being significant: the highest (absolute) z-value is 1.2. These findings unambiguously support the hypothesis that the effects of R&D support are materialized within one year after the end of treatment. They are also consistent with results obtained by Lanjouw and Mody (1996) and Griliches (1998), who observe that patent applications tend to be taken out early in the life of a research project.

So far, we have classified the source of funding of public support by the main policy instrument, i.e. whether the largest source of funding is direct subsidies or tax credits. However, one might think that approval from multiple public agencies may signal a high quality of the project. The existing literature provides little evidence on this issue. For example, Bérubé and Mohnen (2009) find that firms which receive direct R&D subsidies in addition to R&D tax credits are more innovative than firms which only receive tax credits. In contrast, Czarnitzki and Lopes-Bento (2013) find that the estimated treatment effects do not depend on dummy variables related to the presence of a subsidy mix.

Similar to Czarnitzki and Lopes-Bento (2013), we examine the issue of support mixture by means of (ad hoc) dummy variables. Specifically, we introduce one dummy variable taking

[30] If a firm is assigned to a new treatment or is no longer observed (firm-exit), the post-treatment period is truncated accordingly (cf. Footnote 24).

the value one if *two* public agencies provide support for the same treatment and another dummy variable which is one if the project is supported by all three sources (IN, RCN and SKF). We include a full set of interactions between these two dummy variables and the dummy variables indicating the main policy instrument. The result of the estimation is that we do *not* reject our original specification. The p-value of the test is approximately 0.6, which is clearly insignificant. This result is likely to reflect that treatments with SKF as main policy instrument rarely include funding from IN or RCN, whereas treatments with direct subsidies as main policy instrument, often include tax credits as a secondary source of funding. This is illustrated in Table 10. In the upper part of the table, we see that in the case of treatments with direct subsidies (DIR) as the main policy instrument (main source of funding), support from SKF is received in 42 percent of the corresponding treatment-years. In the case of treatments with SKF as the main policy instrument, support from DIR is received in only 8 percent of the corresponding treatment-years.

Looking at the amount of support reveals a striking difference between the policy instruments (lower part of Table 10): In the case of treatments with direct subsidies (DIR) as the main policy instrument, 74 percent of total funding comes from DIR. In the case of treatments with SKF as the main policy instrument, 85 percent of total funding comes from SKF. The conclusion from Table 10 is that projects *mainly* supported by direct subsides often obtain tax credits too, but not vice versa.

TABLE 10 HERE

5 Conclusions and policy implications

We have analysed the three major sources of direct and indirect R&D subsidies in Norway: direct subsidies from Innovation Norway and the Research Council of Norway, and the R&D tax credit scheme *Skattefunn*. Our analyses are based on a quasi-experimental design, where we mimic – through a stratification-based matching procedure – the conditions of a randomized experiment, using measures of pre-treatment R&D activity, patenting, firm-size, firm-age, industry and region as stratification variables.

Innovation policies to support private R&D activities should ideally reflect the size of the external spillovers from the research. Direct grants from the Research Council and Innovation

Norway are targeted specifically towards projects with low private return and possibly high social return, such as e.g. the development of environmental and medical technologies. Targeting R&D subsidies specifically towards prioritized technology areas that generate larger externalities is thus likely necessary in order to foster major innovation leaps and new technologies that are not already close to the existing market solution.

In contrast to direct grants, tax credits are generally thought to give more incentives to SMEs – as they are typically more exposed to financial constraints than large firms – and to firms with little R&D activity before obtaining support – due to a cap on the tax deductions.

In our empirical analyses, we found that both direct subsidies and tax credits have significant positive effects on patent applications as well as granted patents. However, the magnitude of the effects depend critically on the firms' pre-treatment characteristics. All our statistically significant estimates (at the 5 percent level) are related to the extensive margin, i.e. firms with no patent applications prior to obtaining support. We find little or no evidence that other variables, such as firm-size or firm-age, have a separate impact on the efficiency of the support when we control for the pre-treatment level of R&D activity and patenting.

We find that direct subsidies have triggered at least three times as many granted patents per NOK million of support compared to tax credits. The entire effect pertains to firms that are R&D-*inactive* prior to obtaining support. Therefore, the usual explanation, that tax credits provide less incentives for innovation than direct subsidies for R&D active firms, especially large ones, does not apply here. Rather, our results indicate that projects that are (mainly) supported by direct subsidies have a higher potential for innovation than projects that are (mainly) subsidized by tax credits.

Our analyses lead to rather strong policy implications. Support to historically innovating firms do not spur further innovations, at least not patentable ones. The reason may be that the supported projects are carried out regardless of the support (cf. Footnote 17). Instead, support should be directed to promote innovations at the extensive margin, i.e. to firms with a high potential of becoming innovative rather than to firms that already have a record of being innovative. Moreover, as targeted subsidies generate more innovations, society benefits from distributing much of the subsidies to priority areas.

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TABLES

Table 1. Share of R&D support, patent applications and firm-years. In percent, by industry region and firm-size

Classification variable	Direct support	Tax credits	Patent appl.	Firm-years
<u>Industry</u>				
Primary industries	2.9	3.8	0.4	1.6
Mining, oil and gas extraction	1.3	1.0	5.0	0.5
Manufacturing	29.0	31.9	39.7	6.1
-Textiles and food	3.7	4.9	1.7	1.2
-Wood, pulp and paper	1.1	1.7	0.9	1.1
-Chemicals, pharma., rubber, plastic	5.0	4.1	6.5	0.4
-Metals, minerals	4.9	5.2	3.4	1.2
-Machinery and electronics	14.3	16.0	27.2	2.2
Power prod., waste and recycling	1.6	1.6	1.1	0.9
Information and communication	11.9	25.2	3.8	4.2
Professional, scientific and technical services	41.0	21.7	34.3	10.8
Other services	12.3	14.9	15.8	75.9
<u>Region</u>				
South	5.3	5.1	6.6	6.0
East	43.8	49.4	48.3	52.5
West	27.2	28.1	34.0	25.8
Middle	18.2	11.1	8.6	7.6
North	5.6	6.4	2.5	8.2
<u>Firm-size</u>				
Small (<50 employees)	64.2	82.5	63.0	98.1
Medium (50-249 employees)	22.6	13.9	13.5	1.6
Large ($\geq$250 employees)	13.2	3.6	23.5	0.3

Table 2. Mean/median of key variables at the firm-year level (upper part) and summary statistics (lower part). All vs. patenting firms in the Business Register, 2002-2013

Variables	All firms		Patenting firms[1]	
	Mean	Median	Mean	Median
No. of patent applications	0.002		0.24	
No. of granted patents	0.002		0.18	
Treated firm (0/1)[2]	0.037		0.57	
No. of employees	7.4	1	85.8	5
Labor productivity[3]	0.43	0.36	0.56	0.51
Return on assets[4]	0.060	0.041	0.021	0.030
Capital intensity[5]	1.40	0.58	2.39	1.39
Firm-age	10.5	7	12.5	9
Firm-age ≤ 3 (0/1)[6]	0.30		0.22	
No of firm-years	2,088,033		17,370	
No of firms	335,763		2,024	
No of treated firms	8,834		1,081	
Total support (NOK billion)	21.9		7.5	
No. of patent appl.	4,230		4,230	
No. patent appl. by treated firms	2,969		2,969	
No. of granted patents	3,226		3,226	
No. of granted patents by treated firms	1,744		1,744	

Notes: 0/1 indicates a firm-year dummy variable. [1] Firms with at least one patent application during the period. [2]Equal to 1 in all years if the firm received support at least once. [3] Value added per employee in NOK million (NOK 100 $\approx$ EUR 11 during 2002-2013). [4]Operating income divided by the book value of total assets. [5]Tangible fixed assets in NOK million per employee. [6] Equal to 1 if the firm is $\leq$ 3 years old

Table 3. Treated firms in the Business Register: total R&D support and descriptive statistics at the time of treatment assignment

	All treated firms		Treated firms with R&D info[1]	
No. of treated firms	8,834		6,838	
No. of treatment-years [2)]	27,224		23,737	
Firm-years with IN support	4,362		3,141	
Firm-years with RCN support	3,646		3,172	
Firm-years with SKF support	23,049		21,053	
Total support (NOK billion)	21.9		19.1	
Total IN support	5.0		4.1	
Total RCN support	6.4		5.0	
Total SKF support	10.5		9.9	
No. of patent applications	2,969		2,017	
Descriptive stat. (treated firms)[3]	Mean	Median	Mean	Median
Previous patent appl. (0/1)[4]	0.11	0	0.12	0
No. of employees	32.1	5.0	39.7	7.0
Labor productivity [5]	0.45	0.40	0.46	0.41
Return on assets[6]	0.010	0.020	0.020	0.030
Firm age	8.6	5.0	9.0	5.0
Firm age ≤ 3 (0/1) [4]	0.43	0.00	0.43	0.00
Capital intensity[7]	1.63	0.83	1.61	0.83
R&D-active (0/1) [4]	NA	NA	0.70	1.0

Notes: The table reports summary statistics for key variables at firm-year level for all treated firms in the Business Register vs. firms in the Business Register merged with R&D data. The lower part of the table gives the mean/median values of key variables at the firm-year level at the time of treatment assignment. [1] From two sources: the annual R&D census and questionnaires to firms with support from SKF [2] Some firms might receive support from several sources. Thus, the total for the rows might be larger than the no. of treatment-years. [3]At the time of treatment assignment [4] Dummy variable. [5]Value added per employee in millions of NOK (100 NOK $\approx$ 11 EUR). [6]Operating income divided by the book value of total assets. [7]Tangible fixed assets in NOK million per employee

Table 4. Balancing properties w.r.t. key variables in the estimation sample at the time of matching. Treated vs. controls and R&D-inactive vs. R&D-active firms [1]

Variables	R&D-inactive				R&D-active			
	Treated		Control		Treated		Control	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Patent appl. before matching (0/1)[2]	0.026	0.004	0.026	0.008	0.045	0.008	0.045	0.008
No. of employees	21.2	2.9	21.4	2.0	39.1	8.1	33.3	5.4
Labor productivity[3]	483	16	448	13	490	40	504	30
Return on assets[4]	0.04	0.01	0.06	0.00	0.04	0.02	0.05	0.01
Capital intensity[5]	1454	145	1484	38	1762	109	1857	179
Firm-age	9.9	0.3	8.9	0.7	10.6	0.5	9.6	0.5
Firm-age ≤ 3 (0/1)[6]	0.42	0.02	0.46	0.04	0.27	0.02	0.35	0.02
Small firm (0/1)[7]	0.89	0.01	0.91	0.01	0.87	0.03	0.87	0.03
Medium firm (0/1)[8]	0.09	0.01	0.08	0.01	0.10	0.02	0.11	0.02
R&D support and sample size 2002-2013:								
No. of firms	1,134		68,930		2,528		2,970	
No. of treatment-years	3,406				10,122			
No. of firm-years with DIR subsidies	1,117				2,276			
No. of firm-years with SKF credits	2,747				9,203			
Total support (NOK billion)	3.3				7.7			
Total DIR subsidies	2.1				3.4			
Total SKF credits	1.2				4.3			
No. of patent appl. 2002-2013	328		283		2,113		424	

Notes: 0/1 indicates a firm-year dummy variable. [1] Frequency weighted averages of cell-specific means at the time of matching, with weights equal to no. of treated firms in each cell. [2] Equal to 1 if the firm has at least one patent application prior to treatment assignment; the patent variables date back to 1995. [3]Value added per employee in NOK million (100 NOK $\approx$ 11 EUR). [4]Operating income divided by the book value of total assets. [5]Tangible fixed assets in million NOK per employee. [6]Equal to 1 if the firm is $\leq$ 3 years old. [7]Equal to 1 if the firm has <50 employees. [8]Equal to 1 if $50 \leq \text{employees} < 250$

Table 5. Effects of innovation policies on patent applications. Estimates of the treatment response functions $\gamma(x)$ and $\pi(x)$ using the matching and fixed effects (FE) estimator, by main policy instrument and firm classification

Policy	Firm classification (x)		Matching estimator		FE estimator[1]	
	Prior patents	Prior R&D	Est.	z-value	Est.	z-value
Direct subsidies	No[2]	Inactive[3]	6.2 ***	13.3	1.14 **	2.38
	No	Active	1.4 ***	5.6	1.16 ***	3.11
	Yes	Active	1.4	1.7	-0.11	-0.84
Tax credits	No	Inactive	3.7 ***	8.0	0.97 **	2.14
	No	Active	0.7 ***	3.7	1.22 ***	6.20
	Yes	Active	0.7	1.1	0.24	1.02
#Treatment-years						
	No	Inactive	2,771		569	
	No	Active	7,752		1,228	
	Yes	Active	580		3,661	
# Patent appl.[4]			2,724		3,193	
# Treated firms			3,662		664	
# Firms			75,562		1,470	

Notes: ***, ** and * denote, respectively, significant estimate at the 10, 5 and 1 percent level. [1]The FE sample includes patent data for the pre-support schemes period 1995-2001[2] Firms with zero patent application prior to treatment assignment, based on patent data since 1995. [3] Firms with zero R&D-activity before obtaining support. [4]During 2002-2013

Table 6. Effects of innovation policies on granted patents. Estimates of treatment response functions $\gamma(x)$ and $\pi(x)$ using the matching and fixed effects (FE) estimator, by main policy instrument and firm classification

Policy	Firm classification (x)		Matching estimator		FE estimator[1]	
	Prior patents	Prior R&D	Est.	z-value	Est.	z-value
Direct subsidies	No[2]	Inactive[3]	6.3 ***	11.2	1.23 **	2.03
	No	Active	0.8 **	2.2	1.41 ***	4.61
	Yes	Active	1.1	1.1	-0.10	-0.67
Tax credits	No	Inactive	2.9 ***	6.1	0.82	1.70
	No	Active	0.5 **	2.1	1.18 ***	5.50
	Yes	Active	0.6	0.7	0.13	0.71
#Treatment-years						
	No	Inactive	2,771		252	
	No	Active	7,752		673	
	Yes	Active	580		2,113	
# Granted pat.[4]			2,040		2,380	
# Treated firms			3,662		570	
# Firms			75,562		1,187	

Notes: ***, ** and * denote, respectively, significant estimate at the 10, 5 and 1 percent level. [1]The FE sample includes patent data for the pre-support schemes period 1995-2001[2] Firms with zero patent application prior to treatment assignment, based on patent data since 1995. [3] Firms with zero R&D-activity before obtaining support. [4]During 2002-2013

Table 7. Estimated Average Marginal Effect (AME), Sum of Marginal Effects (Sum ME) and expected number of patents per year given treatment (μ), by main policy instrument and firm classification. Estimates derived from the matching estimator

Dep. variable	Firm classification (x)		Main policy instrument							
	Prior patents	Prior R&D	Direct support				Tax credits			
			AME	95% CI[1]		μ	AME	95% CI[1]		μ
No. of appl.	No[2]	Inactive[3]	0.15 **	0.02	0.29	0.15	0.01***	0.01	0.00	0.01
	No	Active	0.02 ***	0.01	0.03	0.03	0.01***	0.01	0.01	0.02
	Yes	Active	0.21	-0.26	0.68	0.61	0.00	-0.28	-0.21	0.31
No. of granted	No	Inactive	0.13 **	0.01	0.24	0.13	0.01**	0.00	0.02	0.01
	No	Active	0.01 ***	0.00	0.02	0.02	0.01***	0.00	0.01	0.01
	Yes	Active	0.12	-0.29	0.53	0.45	-0.02	-0.22	0.19	0.24
			Sum ME	95% CI			Sum ME	95% CI		
No. of appl.	No	Inactive	129 **	10	248		28***	12	45	
	No	Active	52 ***	18	86		91***	46	136	
	Yes	Active	58	-90	206		20	-103	143	
	Sum		239				139			
No. of granted	No	Inactive	120 **	12	228		10**	1	19	
	No	Active	17 ***	5	30		53***	25	81	
	Yes	Active	20	-46	86		-7	-82	69	
	Sum		157				56			
Support intensity (million NOK)[5]										
			Mean	Med.			Mean	Med.		
	No	Inactive	1.59	0.81			0.42	0.29		
	No	Active	1.43	0.80			0.48	0.37		
	Yes	Active	1.88	1.16			0.59	0.48		

Notes: ***, ** and * denote significant estimates at the 10, 5 and 1 percent level. [1]Confidence interval. [2]Firms with zero patent application prior to treatment assignment, based on patent data since 1995. [3] Firms with zero R&D-activity before obtaining support. [4] 95% confidence interval. [5]Mean and median support per year during treatment in NOK million (100 NOK $\approx$ 11 EUR), by treatment category

Table 8. Estimated Average Marginal Effects (AME) when firm classification includes age (Type I) or size (Type II). Estimates derived from the matching estimator

Dep. variable	Firm classification (*x*)			Main policy instrument					
	Prior patents	Prior R&D	Firm-Type (I, II)	Direct support AME	95% CI[1]		Tax credits AME	95%	CI[1]
			Type I						
No. of appl.	No[2]	Inactive[3]	Incumb.	0.14*	-0.04	0.32	0.01**	0.00	0.01
			Start-up	0.08**	0.01	0.16	0.01**	0.00	0.03
	No	Active	Incumb.	0.03***	0.01	0.04	0.01***	0.01	0.02
			Start-up	0.04***	0.01	0.07	0.01**	0.00	0.02
	Yes	Active	Incumb.	0.39	-0.40	1.18	0.10	-0.02	0.23
			Start-up	0.05	-0.38	0.47	-0.22	-0.50	0.06
No. of granted	No	Inactive	Incumb.	0.12*	-0.04	0.27	0.00**	0.00	0.01
			Start-up	0.08**	0.00	0.15	0.01*	0.00	0.02
	No	Active	Incumb.	0.01**	0.00	0.03	0.01***	0.00	0.03
			Start-up	0.02***	0.00	0.03	0.01**	0.00	0.03
	Yes	Active	Incumb.	0.32	-0.24	0.87	0.13	-0.24	0.87
			Start-up	0.03	-0.32	0.38	-0.18	-0.32	0.38
			Type II						
No. of appl.	No	Inactive	SME	NA			NA		NA
			Large	NA			NA		NA
	No	Active	SME	0.03***	0.01	0.02	0.01***	0.01	0.02
			Large	0.04	-0.02	0.03	0.00	-0.02	0.03
	Yes	Active	SME	0.02	-0.24	0.16	-0.04	-0.24	0.16
			Large	3.19*	-0.43	2.76	1.16	-0.43	2.76
No. of granted	No	Inactive	SME	NA			NA		NA
			Large	NA			NA		NA
	No	Active	SME	0.02***	0.01	0.02	0.01***	0.01	0.02
			Large	0.03	-0.02	0.09	0.01	-0.02	0.03
	Yes	Active	SME	0.05	-0.18	0.27	-0.02	-0.19	0.14
			Large	2.03*	-0.26	4.33	1.15	-0.25	2.55

Notes: See notes to Table 7

Table 9. Post-Treatment Average Marginal Effect (PTAME)[1] by main policy instrument and firm classification. Estimates derived from the matching estimator

Dep. variable	Firm classification (x)		Main policy instrument							
	Prior patents	Prior R&D	Direct support				Tax credits			
			PTAME	z-value	95% CI[2]		PTAME	z-value	95% CI	
No. of pat. appl.	No[3]	Inactive[4]	0.00	0.86	-0.01	0.01	0.00	1	0.00	0.01
	No	Active	0.02	0.88	-0.02	0.06	0.01	0.93	-0.01	0.03
	Yes	Active	-0.01	-1.28	-0.03	0.01	0.00	-0.53	-0.02	0.01
No. of granted pat.	No	Inactive	0.00	0.88	0.00	0.01	0.00	1.22	0.00	0.01
	No	Active	0.02	0.93	-0.03	0.07	0.00	0.54	-0.01	0.01
	Yes	Active	-0.01	-0.84	-0.02	0.01	0.00	-0.52	-0.01	0.01

Notes: [1]Estimated number of additional patents per year during the post-treatment period from $t = T + D_i + 1$ until $t = \min(T + 2D_i, E_i)$, where E_i is the year of attrition or a new treatment assignment. [2]95% CI. [3]Firms with zero patent application prior to treatment assignment, based on patent data since 1995. [4] Firms with zero R&D-activity before obtaining support

Table 10. Share of treatment-years and share of total support, by the treatment's main source of funding

Share of treatment-years with support from	Main source of funding	
	Direct subsidies (DIR)	Tax credits (SKF)
DIR	0.58	0.08
SKF	0.42	0.92
Share of total support from		
DIR	0.74	0.15
SKF	0.26	0.85

Note: If a firm may get support from both sources in the same year, the same firm-year is counted twice when calculated the shares

APPENDIX

Table A.1. After matching: Share of R&D support, patent applications and firm-years. In percent, by industry, region and firm-size category

Classification variable	Direct support	Tax credits	Patent appl.	Firm-years
Industry				
Primary industries	2.7	3.5	0.5	1.6
Mining, oil and gas extraction	1.5	0.9	4.6	0.4
Manufacturing				
-Textiles and food	4.1	5.2	1.4	1.5
-Wood, pulp and paper	1.4	1.9	1.3	1.5
-Chemicals, pharma., rubber, plastic	4.4	3.3	2.5	0.4
-Metals, minerals	7.4	4.6	3.3	1.5
-Machinery and electronics	16.3	16.0	29.3	2.4
Power prod., waste and recycling	1.4	1.3	0.6	0.7
Information and communication	16.0	27.0	5.1	5.3
Professional, scientific and technical services	34.2	21.6	36.3	12.0
Other services	10.8	14.7	15.2	72.8
Region				
South	6.0	5.2	9.0	5.5
East	53.3	52.2	52.4	56.6
West	27.2	27.7	31.2	24.7
Middle	11.1	10.2	6.0	6.7
North	2.4	4.7	1.4	6.6
Firm-size				
Small (<50 employees)	65.9	83.2	64.4	96.9
Medium (50-249 employees)	14.1	12.8	13.2	2.6
Large (≥250 employees)	20.1	4.0	22.4	0.5