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Innovation outcomes of public R&D support: A new approach to identifying output additionality

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Abstract

What difference does government support of business R&D make to the rate of innovation? Addressing this important question has deep theoretical roots and broadening practical applications in OECD countries. The analysis of output additionality has been hampered by incomplete data combined with adaption of problematic methodologies. In this light, we contribute to the formative literature in three main ways: we analyze comprehensive panel data of Norwegian enterprises over a 20-year period; we include trademarks and industrial designs as well as patents to broaden measures of innovation output; and we apply machine learning methods to estimate treatment effect functions, thereby addressing the problem of a practically unlimited number of potential confounding factors. Our findings support and elaborate earlier work that fiscal stimulus tends to have greatest impact on previously non-innovative firms. The impact of support measures, alone or in combination, is on the extensive rather than intensive margin. For previously R&D-active firms, our results indicate that public support has low additionality and even risks crowding-out private financing of R&D.

Keywords: Innovation, R&D support, Output additionality, Intellectual property rights, Patents, Trademarks, Public policy instruments, Lasso, Double selection, Poisson regression

JEL classification: C33, C52, O31, O34, O38

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Sammendrag

Hvilken effekt har FoU-støtte til næringslivet på innovasjonstakten til bedriftene? Dette er et viktig spørsmål med historiske røtter og stor praktiske betydning. Analyser av *output addisjonalitet* av FoU-støtte har vært hemmet av ufullstendige data kombinert med iboende metodologiske utfordringer. På bakgrunn av dette bidrar vi til litteraturen på tre måter: vi analyserer omfattende paneldata fra norske bedrifter over en 20-års periode; vi inkluderer varemerker og industriell design, så vel som patenter for å utvide målene for innovasjonsutfall, og vi anvender maskinlæringsmetoder for å estimere kausale effekter. Våre funn støtter og utdyper tidligere arbeider som viser at finansielle stimuli har størst innvirkning på tidligere ikke-innovative bedrifter. Vi identifiserer signifikante effekter av støttetiltak, hver for seg eller i kombinasjon, på den ekstensive marginen snarere enn den intensive. For tidligere FoU-aktive bedrifter indikerer våre resultater at offentlig støtte har lav addisjonalitet og risikerer å fortrenge privat finansiering av FoU.

1 Introduction

Governments have long sought to induce the private sector to invest more in research, development and innovation. The immediate aim is to stimulate firms to innovate more, the longer-term policy goal is to promote productivity. The slowdown in productivity growth in recent decades ("the great productivity slowdown") has again focused policy attention on how to improve the effectiveness of R&D support policies. This renewed attention has been further spurred on by changing climate challenges and other policy priorities. As a result, R&D support measures have become more widespread, more pronounced, and more diverse than ever before.

OECD countries spend 0.21 percent (as of 2021) of their combined GDP to subsidize private R&D activity, principally via traditional 'direct' channels (grants) but also increasingly via measures involving the tax system. Rooted in a familiar two-handed premise, there is a strong case for this public R&D support.[1] A decades-long empirical literature has helped governments to evaluate the effects of R&D support. It has done so in a variety of ways, at different levels and from different angles (e.g. Dimos and Pugh, 2016). The consensus is that the impact of R&D support is, broadly speaking, positive (e.g. Lucking et al., 2019). R&D tax credits and direct public funding 'seem the most effective measures in innovation policy toolkit' (Bloom et al., 2019).

In practice, governments face a challenge to ensure that their investments have the best possible impact for their economies. As they actively adjust the level of support and the way this support is balanced between direct and indirect policies, policymakers want to better understand what works, for which firms, and under what conditions. This is the more challenging in the current context in which a broader range of firms are eligible for more support from a broader range of policy instruments. To help governments to intervene effectively, there is a recognized need to better understand the effects that the full range of R&D grants and tax credits is having on innovation in the private sector (OECD, 2021) and, more specifically, the effects that this range of support is having on different types of firms or industries (Appelt et al., 2022).

This paper revisits the extensive empirical work that has evaluated the impact of fiscal R&D incentives in this light. Our goal is to better understand the effects that the full range of R&D grants and tax credits is having on innovation in the private sector. Here, we build on extensive empirical work that has evaluated the impact of fiscal R&D incentives across several decades and in different jurisdictions. This wide-ranging literature has generally decomposed the question of impact into a number of effects, starting with how reducing the cost of R&D for the firm affects its investment – input additionality (see e.g. Becker, 2015; Hægeland and Møen, 2007; David et al., 2000); how it affects the longer-term innovative behavior of the firm – behavioral additionality (Clausen, 2009); how it contributes to knowledge spillovers (Myers and Lanahan, 2022; von Brasch et al., 2021; Lucking et al., 2019), and, finally, how it affects innovation

[1]On the one hand, economic growth reacts positively to increased R&D, but, on the other, firms tend to underinvest in these activities due to a number of market failures. The policy aims are consistently acknowledged in the literature. See, for example, Almus and Czarnitzki (2003)

outcomes – output additionality (e.g., Cappelen et al., 2012; Takalo et al., 2013; Bronzini and Piselli, 2016; Nilsen et al., 2020).

Our contribution is specifically directed towards the last strand of literature. The output additionality work is relatively underdeveloped in the extensive frame of work that has evaluated the effects of R&D support in recent decades, especially when it comes to innovation outcomes. In part, this reflects the special set of challenges related to the basic questions of what outcomes can be categorized as 'innovation'. In addition, the results of output-additionality studies have tended to be more mixed than that of the more standard input-additionality work. For example, 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. On the other hand, R&D subsidy program were found to have a positive effect on patenting in northern Italy (Bronzini and Iachini, 2014 and Bronzini and Piselli, 2016), and tax credits to increase the propensity to patent in the UK (Dechezleprêtre et al., 2016).

We argue that it is becoming more important to overcome the recognized challenges and to focus on better understanding the effects R&D policies have. The capacity of governments to intervene effectively is impaired by ambiguity about how to target potential innovators (they are notoriously heterogeneous) and what output to prompt (innovation is intangible and hard to measure adequately). Moreover, as policymakers adapt their strategies— for instance, to better stimulate certain forms of innovation (e.g. green technology), it becomes more important to better understand not only whether the support 'unleashes' a sufficient degree of additional expenditure by the firm, but to what extent the support sparks an increase in the innovation output of the firm.

This paper specifically evaluates the effects that the full range of R&D grants and tax credits in Norway is having on the rate of innovation in the private sector. In line with the 'new economics of industrial policy', we reapproach the existing output additionality work in a way that emphasizes improved measurement, the careful application of causal inference, and a more 'nuanced and contextual understanding of the effects of industrial policy' (Juhasz et al, 2023). Building explicitly on earlier work, such as Nilsen et al. (2020), we contribute to the literature on output additionality in four main ways. First, building on previous work that have used Norwegian registry data (Cappelen et al., 2010; Cappelen et al., 2012; Bøler et al., 2015; Nilsen et al., 2020) we compile a detailed and comprehensive firm-level panel data for the total population of Norwegian firms. Second, we contribute to the output additionality literature in terms of how we measure innovation output. We extend the firm-linked innovation measures for the population to trademark and design rights as well as patent applications following recent analysis (see Iversen and Herstad, 2022), to account for differing strategies in IPR protection across industries. A third contribution is that we analyze the effect of *all* sources of R&D subsidies in one country over a 20-year time period, from 2002-2021.

Fourth, and crucially, we contribute to the output additionality literature in terms of methodology: we apply novel machine-learning methods to address and overcome recognized problems associated with endogenous selection. This involves extending an approach pioneered by Belloni et al. (2016) and Chernozhukov et al. (2018), to apply statistical methods to identify the most important control variables when the number of potential confounding factors is practically unlimited.

Our results show that both direct subsidies and tax credits have significant positive effects on intellectual property rights (IPR) applications. However, the effects depend critically on the firms' pre-treatment characteristics. We find that the public policies only give incentives for more IPR among previously R&D-inactive firms, especially startups. When we control for firms' R&D experience and their IPR history, we find no evidence that other variables, such as firm-size, have a separate impact on the effect of the R&D-support schemes. For previously R&D-active firms, our results show that public support has low – and statistically insignificant – additionality and could even partly crowd-out private financing of R&D.

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 empirical model is presented in Section 3, the estimation strategy involving machine learning in Section 4, and the results in Section 5. Finally, Section 6 concludes and suggests some policy implications.

2 Background

We start by briefly reviewing the policy and institutional context in which public R&D support is implemented and what motivates the intervention (declared policy goals). In general, we note that governments are more than ever actively investigating how to induce the private sector to invest more in research, development and innovation (R&D). In taking stock of factors that shape the 'subsidy-induced R&D output', a fundamental question is what 'output' the individual subsidy is designed to induce.

In general, the rationale for government intervention is recognized and well supported in theory. Dimos and Pugh (2016) highlight the importance of the theoretical context and competing perspectives while other review articles (e.g., Cerulli, 2010) discuss the various theoretical interpretations. More immediately, the reason governments use taxpayers' money to support private R&D is to stimulate innovations. That is, new products (goods or services) and/or processes that the enterprise would not otherwise have invested in and developed.[2]

Government support currently takes a range of forms to this end.[3] The two most important ones are tax incentives (primarily tax credits) and direct support (primarily grants). Although the immediate aim is broadly similar, the outcomes that the two types of support target could differ quite dramatically. These differences are important to the way each type of intervention works in terms of the eligibility criteria, the size of —and the conditions for— the subsidy, the expected outcome, etc. In turn, these differences will affect how we measure and model output additionality.

[2]Although we focus on goods and services in this paper, the Oslo Manual (2018) provides for a more comprehensive set of categories.

[3]OECD countries use a variety of R&D subsidies including tax incentives (credits, deductions, reduced rates, tax offsets), direct grants, direct funding, co-funding, and loans.

2.1 Policy approaches

In terms of theory, several traditions among academic economists are noteworthy since they tend to influence how the policy instrument targets eligible firms (e.g., focusing on traditional R&D intensive industries or on other innovative enterprises) and how it seeks to promote innovation outcomes, either through competition or as a rights-based support scheme. R&D support can thus be motivated by more than one expressed aim. The objectives of these policies may differ in substance and scale. A more immediate implication emerges for our study. When policymakers attempt to induce R&D activity, the choice (direct or indirect subsidies) will affect (i) who qualifies for the R&D support and (ii) what innovation outcomes are expected.

The first issue (eligibility) will affect methodological considerations, specifically sample-selection problems. The second issue, which brings into question the type of innovation output that is targeted, will also affect methodological considerations, primarily how to conceive of 'output' and thus how to measure or proxy it.

2.2 Study context

As a country traditionally based on natural endowments (fisheries, forestry, mining, and more recently petroleum) and characterized by many small firms, Norway has in recent decades made a concerted effort to raise BERD as share of GDP. Government strategy reflects the traditional goals of the country (moving up the ranking of innovative countries, shifting more R&D investment from the public to private sectors via cross-sectoral collaboration). [4] A more recent aim has emerged alongside these perennial goals. Norwegian innovation policy has increasingly tried to mark a transition from Norway's role as the largest oil producer in Western Europe to its ambition of becoming a leading knowledge-based economy. This effort can be linked to the development of direct R&D subsidies, with emphasis on sustainability and innovation. Recent Norwegian policy has increased direct funding for R&D that particularly targets research into renewable energy, sustainable fisheries, and climate change mitigation. In this setting, Norwegian R&D support policy has actively adjusted the balance it strikes between direct and indirect subsidies in recent years.

International trends form the background for changing Norwegian policy. Public R&D support (direct government funding and government tax support for business R&D) has increased from 0.16 percent of GDP for OECD countries in 2006 to 0.21 percent in 2021.[5] According to the most recent OECD data direct funding accounted for roughly half of this substantial investment. Tax incentives, meanwhile, have become much more important in this frame since 2000, encompassing 33 of 38 OECD countries in 2023

[4] See the Government long term plan for reseach and higher education https://www.regjeringen.no/no/tema/forskning/innsiktsartikler/langtidsplanen-for-forskning-og-hoyere-utdanning-2023-2032/id2929453/ (in Norwegian)

[5] See https://www.oecd.org/content/dam/oecd/en/topics/policy-sub-issues/r-d-tax-incentives/oecd-rd-tax-highlights.pdf

and accounting for more than half of the R&D support.

Norway is a notable case in this context. R&D support policy has been a key means to raise R&D intensity towards the OECD average, particularly by stimulating the private sector to invest more. Thus, government stimulus has expanded faster in Norway than the OECD average since 2006. Norwegian R&D support of BERD made up ca 0.20 percent of GDP in 2021, close to the OECD average of 0.21 percent. The more active policy has been only a partial success. Total expenditure on research and development, including the government and university and higher education sector, has risen from 1.7 percent of GDP in 2013 to 2.0 percent in 2021.[6] But this is still substantially lower than the OECD average of 2.7 percent in 2021 (up from 2.4 percent in 2013). Norway has at the same time managed to increase the BERD relative intensity from 0.78 percent of GDP in 2013 to 0.91 percent in 2021, which is far away from the longtime public policy goal of 2 percent BERD relative to GDP founded in the so-called Lisbon-strategy. [7]

R&D support in Norway has traditionally been given mainly through direct grants (Hægeland and Møen, 2007). However, this has changed considerably during the past 20 years. Indirect and direct forms each account for almost half of total support, very much in line with the OECD average. We introduce the two types of support, while referring to the extensive literature that describes it in detail. Direct subsidies take the form of direct grants to eligible firms in Norway. Here, the most important funding sources are the Research Council of Norway (RCN) and Innovation Norway (IN).[8] RCN operates larger programs designed to build long-term knowledge, stimulate innovation, enhance value creation, and, more lately, to address societal challenges. RCN grants tend to co-fund up to 50 percent for the supported projects. Norwegian firms obtaining support from RCN tend to concentrate into certain sectors, geographical localtions and among larger firms, with implications discussed below.

IN provides direct subsidies in the form of grants, loans, and guarantees, for priority areas such as environmental technologies. IN specifically targets small start-up firms through designated grants and specialized programs. By allocating support through regional offices, IN prioritizes an equal distribution of support across the main regions of Norway.[9]

The right-based R&D tax credit scheme *Skattefunn* (SKF) was introduced in 2002 to target SMEs, but was extended to all firms in 2003. SKF was introduced to provide more stable conditions for the business community than direct grants (see Cappelen et al., 2010). The tax credit amounts to 20 percent of R&D expenses up to a cap. The cap was NOK 4 million until 2008, then increased to NOK 5.5 mill. in 2009-2013, and then increased again to NOK 8 mill. in 2014 and 25 mill. 2017. Thus, the maximum tax relief was NOK 800,000 in 2003 (about EUR 100,000), 1.1 mill. in 2009 and has been 5 mill. since 2017. [10]

[6] See https://www.oecd.org/content/dam/oecd/en/data/datasets/main-science-and-technology-indicators/msti-highlights-september-2023.pdf

[7] See https://www.forskningsradet.no/indikatorrapporten/Nyeste-tall/

[8] See Nilsen et al. (2020) for detailed descriptions of both agencies.

[9] See Table 3.5 and Figure 3.3 in Cappelen et al. (2016)

[10] The tax refund takes place at the end of the year when the actual R&D expenses have 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 about the scheme.

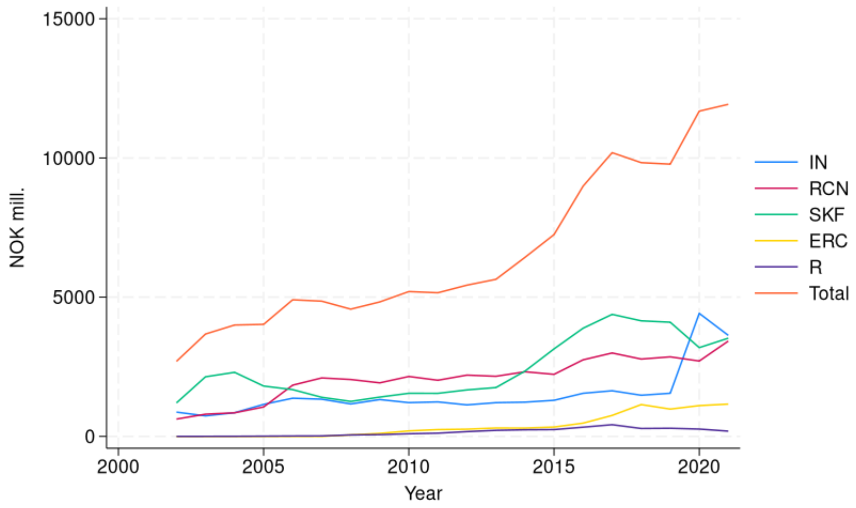

Figure 1: Total annual business enterprise R&D (BERD) support in NOK million from 2002-2021, by source of funding: Innovation Norway (IN), tax credits (SKF), Research Council of Norway (RCN), the European Research Council (ERC) and Regional programs (R). In fixed 2021 prices

The Norwegian tax credit scheme does not discriminate between types of R&D or technologies. In contrast to direct support, it does not target specific technologies according to a policy rationale (e.g., market failure), for instance to promote environmental technologies (Acemoglu et al., 2012; Dechezleprêtre et al., 2013; Calel and Dechezleprêtre, 2016). Tax credits may be better geared towards promoting near-market solutions rather than new technologies that require greater development (David et al., 2000).

Other sources of direct BERD support coexist with IN, RCN and SKF, most notably the European Research Council (ERC) and various regional programs, although they are small in comparison. The relative size and development over time of the different funding agents are shown in Figure 1. The increasing importance of SKF after 2014 is clearly visible. Support from ERC has also become increasingly more important since 2015, by far exceeding support from regional programs (R) since 2017. The spike in IN support from 2020-21 is due to a stimulus package in connection with the pandemic, whereby IN temporarily handed out substantially higher grants than in normal times. In the preceding three years (2017-2019), the share of tax credits over total BERD support was 45 percent.

2.3 Empirical implications

In sum, Norway has tweaked the relative components (direct vs indirect) of R&D support in recent years and now dedicates nearly half of its public stimulus via tax-credits. Direct subsidies are no longer the dominant form of R&D support. This has marked an important shift in policy, which is reflected more generally in OECD countries.

The shift has consequences for how we should analyze output additionality. It affects who is eligible for support, how much support can be received over how long, what sort of projects are involved and what sort of outputs can be expected. These questions affect our choice of datasets, our outcome variables, and our overall approach.

In terms of who receives support, a primary effect of the shift has been to change the composition of firms that receive R&D support (large vs small, manufacturing vs services, more vs less R&D intensive). Broadly speaking, recipients of grants from RCN tend to be larger, older and more R&D intensive than recipients of grants from IN, whereas tax credits – although originally introduced with SMEs in mind – are neutral with respect to firm characteristics. By design, many more firms receive tax credits than grants. In short, the different types of support are exposed to different types of selection biases.

There are also important differences in the type of projects involved and the amount of funding which will affect the type of output which can be expected. Individual projects that receive direct grants from RCN tend to be further away from the market, and in an earlier phase, and receive more support than projects obtaining grants from IN or being supported (only) by tax credits. In addition, there are temporal effects to consider as the frequency and size of the "support dose", will also affect the potential for innovation output.

3 Data sources and description of variables

The composite, firm-linked dataset follows in the tradition initiated by Mairesse and Mohnen (2010). In practical terms, our empirical strategy builds closely on earlier Norwegian studies. Our approach draws on four data sources to build a comprehensive panel dataset for the complete population of Norwegian business enterprises (firms): (i) The Business registry consisting of firm-level data for the full population of active Norwegian limited liability business enterprises. (ii) The Innovation Survey consisting of reported R&D activity from the R&D census questionnaire. (iii) The database on Public support for R&D consisting of detailed information about R&D subsidies from all major programs whether direct subsidies (grants) or tax credits. (iv) Registered IPR applications (patents and trademarks). The source of data set (i)-(iii) is Statistics Norway and of (iv) the Norwegian Industrial Property Office (NIPO), which is responsible for processing applications and approving patent rights, trademarks and designs in Norway.[11] Firm identifiers are provided by Statistics Norway (SSB) and the Nordic Institute for studies of Innovation, Research and Education (NIFU).

These four databases consist of micro-data linked at the enterprise-level. In terms of the construction of this composite database, two major extensions are notable. In comparison with earlier work, we extend the overall period of analyses to 2002-2021 (although some of our data go back to 1995). The extended period traces key dimensions of the underlying industrial organization at the micro-level over the past two

[11] The IPR system in Norway is characterised by a high degree of harmonisation with regulations and practices in Europe and by cooperation with international IPR organisations such as the Nordic Patent Institute (NPI), the European Patent Office (EPO), and the World Intellectual Property Organization (WIPO).

decades, while observing which firms report formal R&D and/or innovation activity, and which firms receive what form of R&D subsidy over time. The observation of previous R&D activity and/or R&D subsidy is central to our identification strategy, as we will discuss.

The second important extension is how we proxy innovation output. The literature on output additionality has tended to proxy innovation output by using measures from R&D or Innovation Surveys (e.g., Mairesse and Mohnen, 2010; Bodas Freitas et al., 2017), or from firm-linked patenting (e.g. Bronzini and Piselli, 2016) or from both (e.g., Cappelen et al., 2012). This paper will indeed include survey-based variables (see above), but not as output variables. Instead, we use registry data on IPR applications as measures of innovation.[12] In contrast, innovation measures based on surveys may be prone to measurement errors as they depend on the respondents' own judgement and accuracy. For example, comparing the data on patent applications from the Norwegian Community Innovation Survey (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.

We first need to measure the level of the firm's R&D activity prior to the receipt of R&D support (pre-treatment period). The ability 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.[13] 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 IPR 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. The same argument applies, of course, if we were to measure innovation outcomes using CIS data. 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 re-

[12]Firms intending to file for patent protection in several countries may apply directly at the European Patent Office (EPO) or the Patent Cooperation Treaty (PCT) to establish a filing date. However, as there is no such thing as an international patent, the applicant must still apply to each national patent authority where they want the patent to be valid. This happens through an administrative procedure involving a translation of the patent document and payment of a fee. About 10 percent of the patent filings in our data set are EPO/PCT filings.

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

garding each of the applicants' R&D expenditures three years prior to applying. These data are collected by the Research Council of Norway and include information on R&D expenditures for most firms included in the *Skattefunn* database.

In sum, the paper combines four firm-linked sets of microdata for all business enterprises in Norway spanning the years from 1995 to 2021, 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 IPR data contain unique firm identification numbers that allow for a reliable match of the IPR data to the other data sets.[14] The data are comprehensive in terms of extent, are highly reliable, and have a high level of validity in terms of relevance and representativeness. This provides a unique vantage point to provide a more complete picture of government efforts to promote business R&D over time.

A detailed data description of key variables is provided below, where they are grouped into three main categories: measures of innovation (Section 3.1), innovation policy instruments (Section 3.2), and determinants of innovation (Section 3.3).

3.1 Measures of innovation

We utilize the three types of industrial IPR ("industrial rights"): patents, trademarks and designs to measure innovation output at the firm level. Our approach thus extends beyond firm-linked patents as an indicator of innovation output. While patents have acknowledged strengths as an indicator of innovation output (strong, positive correlation with R&D activity, as most important innovations are patented), the propensity to patent is skewed towards large firms in a few R&D intensive industries, especially in manufacturing. The weakness of patent measures may be magnified when evaluating the impact of R&D tax credits, which applies indiscriminately to all firms and innovation types, including sectors of the economy with less formal forms of R&D, such as services. This novel approach follows work in other strands of the innovation literature on how, when, where, and why different types of firms use different forms of IPRs when innovating (e.g., Thoma, 2020; EUIPO, 2019).

Recent work demonstrates the utility of using different industrial IPR to analyze different types of innovations (see EUIPO, 2019; Thoma, 2020; Flikkema et al., 2019). To protect their R&D investment, innovative firms adapt their IPR strategies to their market and to the innovation in question. The literature indicates that a combination of patents and other IPR captures more innovative activities in the service sector (e.g., Hipp and Grupp, 2005), and among smaller and/or younger firms, than patents alone.

Trademarking is a more recent proxy for innovation and product differentiation than patents (see review in Schautschick and Greenhalgh, 2016). Firm-level trademark filing behavior serves "to capture innova-

[14] Entity recognition within the IPR data– and name harmonization with other data sources– is challenging (Helmers et al., 2011; Tarasconi and Kang, 2015) In Norway, the Patent Office (NIPO) has collaborated with Statistics Norway (SSB) and Nordic Institute for studies of Innovation, Research and Education (NIFU), a research institute, to ensure that the individual IPR filing is linked to the appropriate business enterprise.

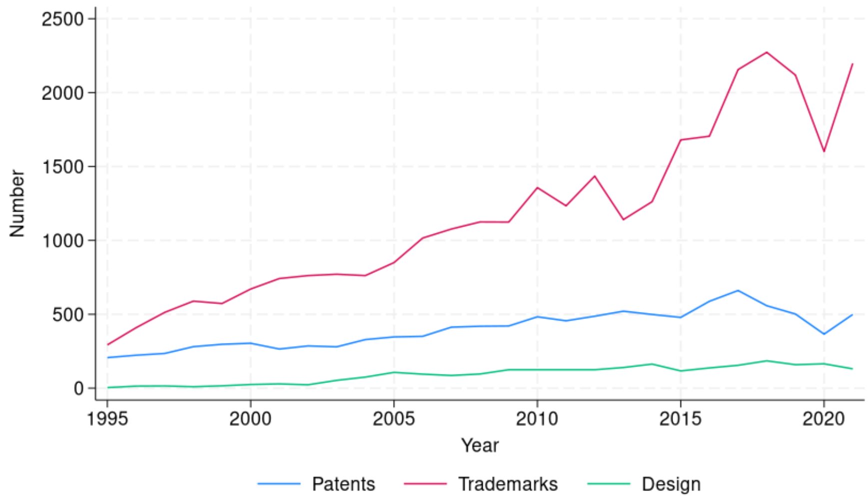

Figure 2: Annual sum of published patent applications, trademarks and designs from 1995-2021 by Norwegian limited liability firms. By year of application

tive activity and future of demand expectations for a relatively large and diverse number of actors" (deGrazia et al., 2020) and is theoretically linked to Schumpeterian technological competition (Greenhalgh and Rogers, 2012; Iversen, 2008). However, not all trademarking reflects innovation and product differentiation. In particular, rising horizontal product variation leads to more trademarking, but not necessarily the creation of genuinely new products and services (e.g., Mangani, 2007).[15]

We see from Figure 2 that the number of patent filings in Norway, by year of application, has followed an upward path since 1995, but interrupted by business cycle fluctuations.[16] There was an overall increase from in 1995–2016, except for a drop related to the bursting of the IT bubble around 2001–2003 and a decline during the Great Recession (2007-2009). Then there was a sharp drop during the years of the pandemic (2020-2021). More conspicuously, the development in trademark rights shows a steep trend, especially from 2014-2021. This is interesting because it coincides with a period of steep increase in public R&D support (see Figure 1). Finally, the number of designs exhibits a weak positive trend over time, and is little affected by business cycle fluctuations or changes in aggregate R&D support.

3.2 Innovation policy instruments

For the econometric analyses we add support from the regional agencies and IN and refer to the aggregate as the Innovation Norway and Regional programs (INR). The aggregation is justified on the grounds that

[15] See the growing literature of trademarking as an indicator of firm-level innovative activities (deGrazia et al., 2020; Castaldi et al., 2020; Greenhalgh and Rogers, 2012; Jensen and Webster, 2009; Mendonca et al., 2004)

[16] About 10 percent of the patent filings in our data set are EPO/PCT filings that are sent to NIPO for subsequent validation. In these cases, we register the application date as the date of the first application (the priority date), not the date the application was received by NIPO for validation.

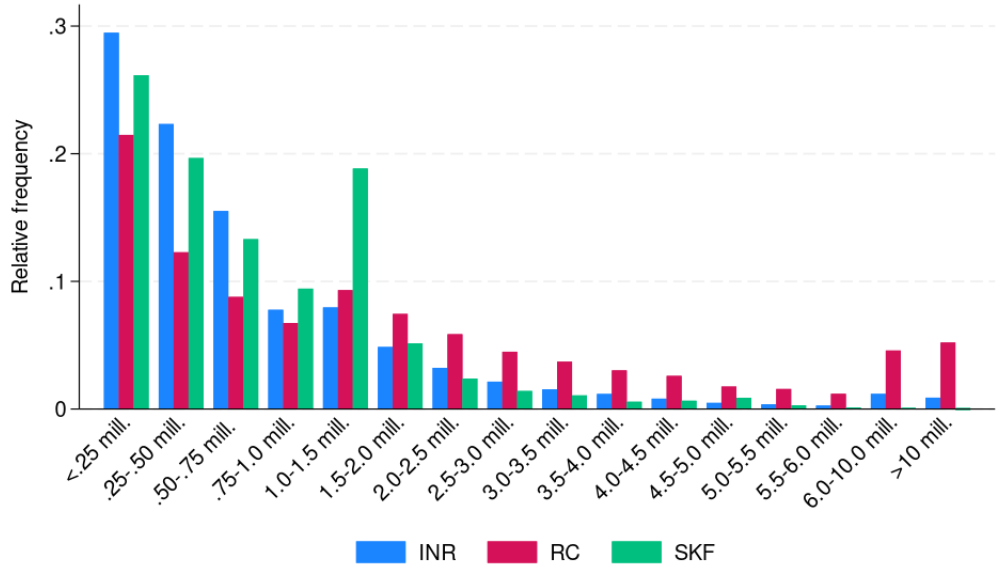

Figure 3: Distribution of amount of support in NOK million per firm-year with support, by policy instrument: IN and Regional programs (INR), tax credits (SKF), and Research Council (RC)

also IN has a strong regional basis. Similarly, we add support from the European Research Council (ERC) and RCN and refer to the aggregate as Research Council (RC).

A distinct difference between the three (aggregated) policy instruments, is that RC support is obtained by much fewer firms, but in much higher amounts per firm-year, than support from INR or SKF. For example, more than 65 percent of firm-years with INR support and 55 percent of firm-years with tax credits are associated with less than NOK 750,000 of support. The corresponding number for RC is 40 percent. In fact, 30 percent of INR grants are given in amounts of less than NOK 250,000 per year, which is a noticeable higher share of small "support doses" than for RC (22 percent) and even SKF (26 percent). At the right tail of the distribution, about 10 percent of RC grants exceed NOK 5 mill. per firm-year, compared to 2 percent of INR grants and 0 percent of tax credits (all transfers being aggregated to the firm-year level). This is illustrated in Figure 3. The spike in tax credits in the bracket from 1-1.5 mill. per firm-year, is related to the large increase in the cap between 2014 and 2017, as mentioned above.

Figure 4 depicts *support intensity*, measured as the share of firm-years with support from INR, SKF, or RC, relative to all firm-years in the given industry (upper chart), age group (middle chart) or in the given size group (lower chart). The industries with the highest support intensity are Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of machinery and electronics; Manufacturing of textiles and food; and Information and communication.

For RC and SKF there is a clearly visible positive relation between firm age and the probability of receiving R&D support. In contrast, for INR the share of start-up firms ($\leq$ 3 years old) that receive support is nearly as high as for all the other age groups combined. This reflects that Innovation Norway specifically

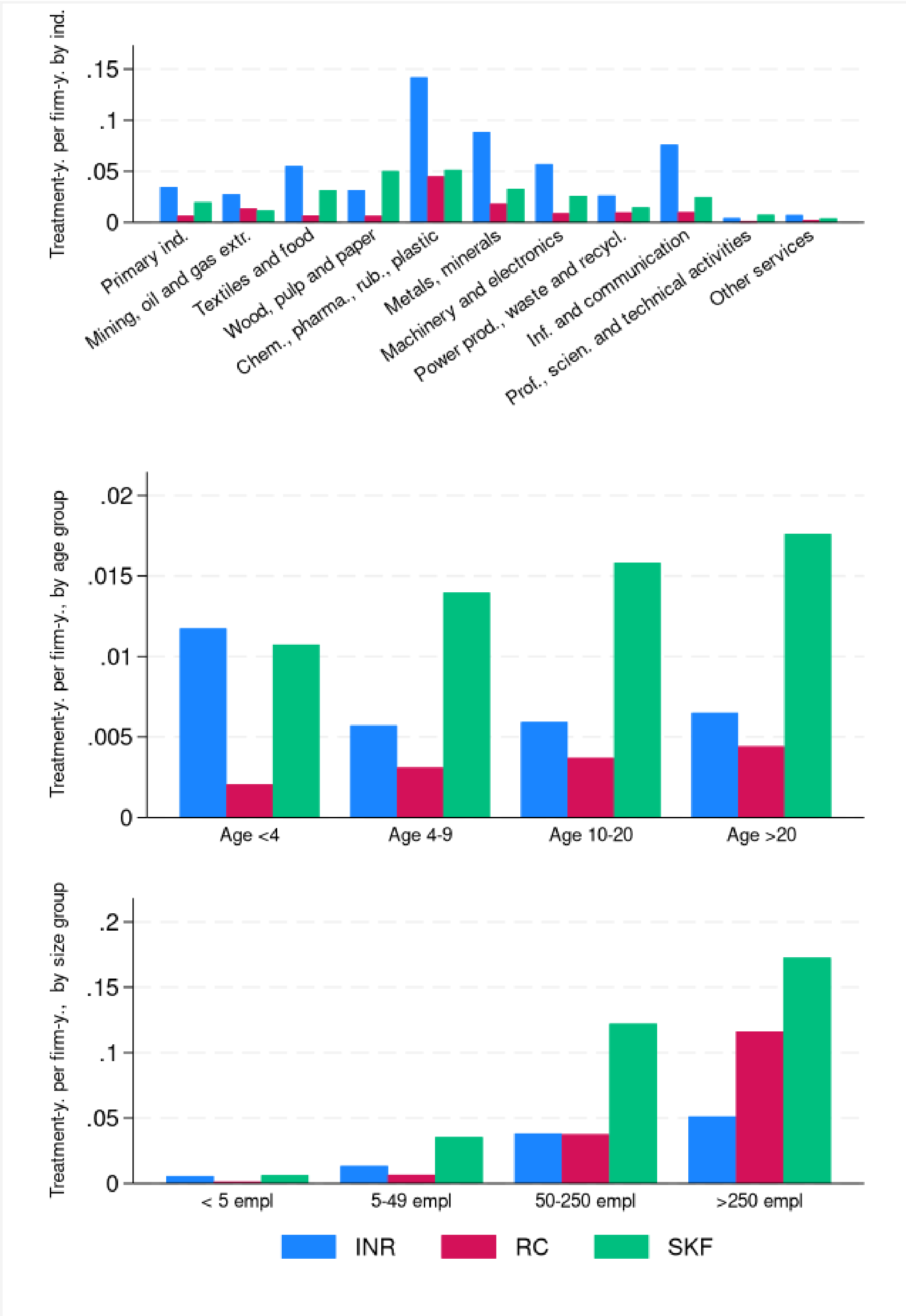

Figure 4: Support intensity. Share of firm-years with support from the given policy instrument, by industry (upper chart), age group (middle chart) and size group (lower chart).

Table 1: Characteristics of the policy instruments with respect to share of support, mean annual support, and number of firm-years with support across firm categories. By policy instrument, firms' R&D experience and firm-age at the year of support. Firm-years with support to limited liability enterprises, 2002-2021.

Policy instr.	R&D-active	Age-group	Share supp.	mean (median) supp.	Firm-yrs.
INR	Yes	Incumbent	50 %	1.38 (0.55)	10,954
	No	Incumbent	17 %	0.79 (0.37)	6,472
	No	Startup	33 %	0.71 (0.47)	14,203
RC	Yes	Incumbent	78 %	4.03 (1.19)	8,695
	No	Incumbent	4 %	1.17 (0.48)	1,698
	No	Startup	17 %	3.10 (0.61)	2,487
SKF	Yes	Incumbent	62 %	0.90 (0.64)	30,376
	No	Incumbent	19 %	0.59 (0.38)	14,285
	No	Startup	19 %	0.63 (0.41)	12,975

Support is sum of R&D support at the firm level in one calendar year, from the given instruments, conditional on positive support. In NOK million (fixed 2021 prices). A startup firm is defined as being at most 3 years in the given year. An R&D-active firm (in the given year) is an incumbent firm with some R&D activity other than (possibly) obtaining support during the previous 5 years.

target small start-up firms and entrepreneurship, as discussed in Section 2.2.

There is a strictly increasing relation between number of employees and the receipt of R&D support (lower chart). In a given year, large firms (>250 employees) have 5, 12 and 17 percent probability of receiving support from INR, RC and SKF, respectively, compared to 2, 1 and 4 percent for firms with 0–49 employees. Thus RC support are much more disproportionally given to large firms relative to small firms, compared to INR or SKF support.

Table 1 further describes the policy instruments, by depicting share of support, mean (median) annual support, and number of firm-years with support across three firm categories for each instrument. Firms are categorized according to R&D experience (R&D-active or not) and firm-age (incumbent or startup). An *R&D-active* firm (in the given year) is an incumbent firm with some R&D activity other than (possibly) obtaining support during the previous 5 years (such as having reported R&D expenditures or IPR filings). For RC the share of support to R&D-active firms is as high as 78 percent. This group of firms also obtains the highest mean annual support, regardless of instrument.

3.3 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 5. The upper chart depicts the average number of published patent applications, trademark filings and designs per firm-year in each industry. Figure 5 also depicts the number of the different types of IPR per firm-year by age group (middle chart) and by number of employees (lower chart).

The upper chart reveals large differences between industries with regard to the propensity to register IPR. The four top industries with respect to patent intensity are Mining, oil and gas extraction; Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of metals and minerals and Manufacturing of machinery and electronics. Other industries have very small numbers of patents per firm-year. With regard to trademark intensity, the four top industries are Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of textile and food products; Manufacturing of metals and minerals and Information and communication. Generally, trademarks are widespread in more industries than is patenting, especially in services and Manufacturing of textile and food products, where patent are rare but trademarks are widespread. Finally, design filings are much less frequent than patents and trademarks overall, and negligible outside the four industries: Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of metals and minerals; Manufacturing of machinery and electronics, and Manufacturing of textile and food products.

The middle chart reveals that there are small differences between the propensity to register IPR across age groups, although firms in the highest age group (>20 years), have slightly higher probabilities than younger firms (on average, about 0.4 pp. higher probability of filing a trademark, 0.2 pp. higher probability of publishing a patent application, and 0.1 pp. higher probability of having a design right than other age groups).

From the lower chart of Figure 5, there appears to be an exponential relation between firm size and the prevalence of patents and trademarks. The number of patents (trademarks) per firm-year is 0.18 (0.23) among large firms, compared to only 0.02 (0.06) among medium sized firms, and less than 0.01 (0.01) among small firms and micro firms. The number of designs per firm-year is only 0.01 among large firms, and negligible in the other size groups.

3.4 Sample size and summary statistics

Table 2 shows summary statistics for the Business Registry, separating between i) all firms, and firms with IPR divided into four groups: firms with ii) IPR (patents, trademarks or designs), iii) patents, iv) trademarks, and v) "IPR bundle", which are firms with patents *in addition* to trademarks or designs. The most striking finding in the upper part of the Table 2 is that approximately 10,000 firms with IPR obtained 60 percent of the total R&D support in 2002-2021, 8,700 firms with trademarks obtained almost 50 percent of total support, 1,800 firms with patents obtained 35 percent of total support and just 639 firms with "IPR bundle" obtained almost 25 percent of total support. These features of the data and their development over time, are illustrated in Figure 6. While it is well known that IPRs are the basis for the valuation of the most successful technology firms in the world, we can safely conclude from Table 2 that there is also a very strong correlation between IPR – in particular patents – and public R&D support. There are almost 5 times

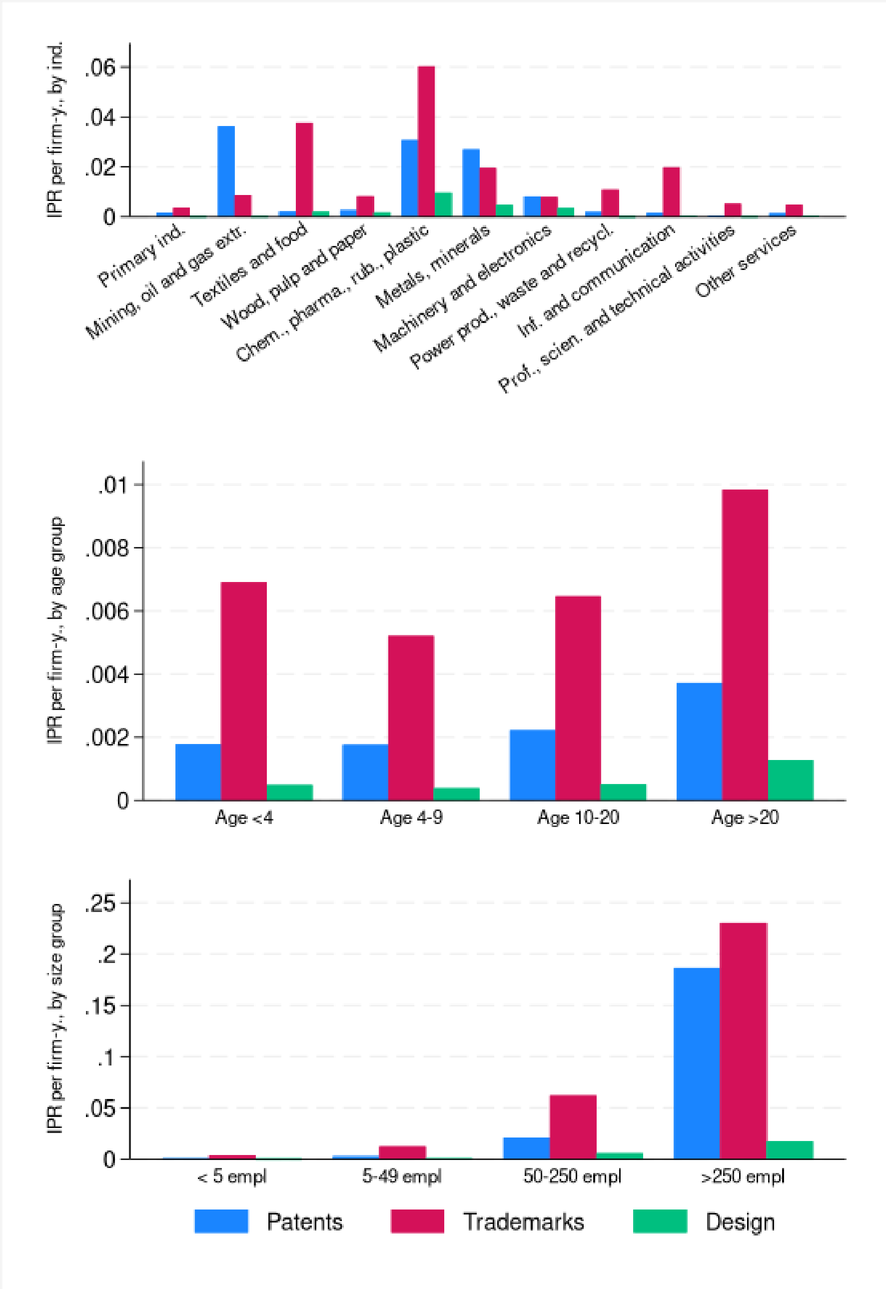

Figure 5: Average number of published patent applications, trademarks and designs per firm-year, by industry (upper chart), age group (middle chart) and size group (lower chart) at the time of application

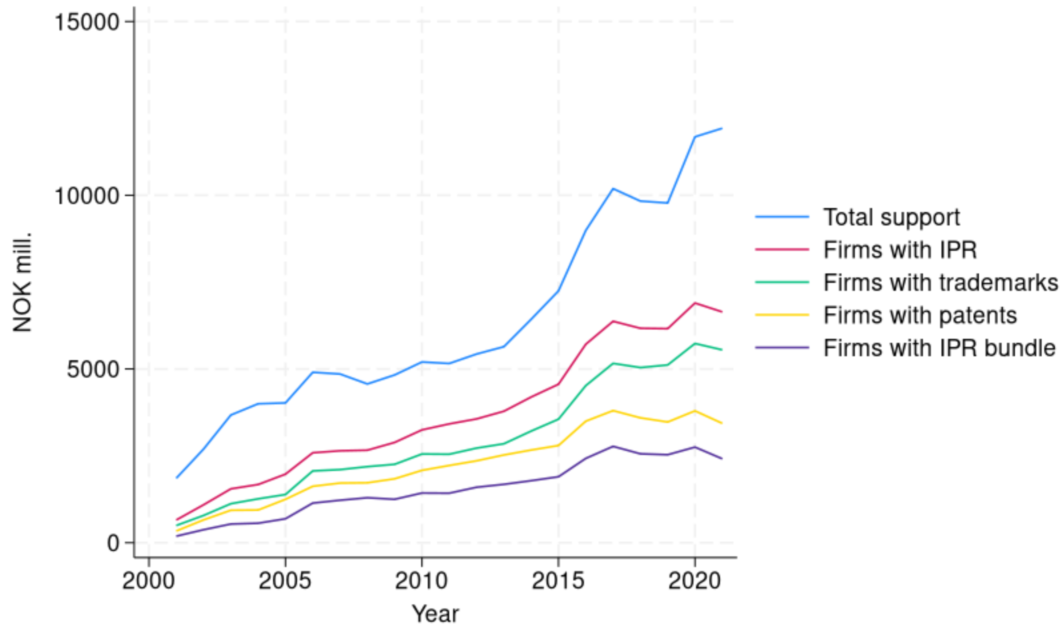

Figure 6: Total annual support in NOK million from 2002-2021 (in fixed 2021 prices). IPR bundle refers to firms with both patents and at least one other type of IPR (trademark or design)

more firms with trademark than patent filings, but they receive only 50 percent more R&D support.

The lower part of the table shows that mean and median firm with IPR applications are much larger than the mean and median for "All firms". They are also somewhat older, but not more profitable. In fact, patenting firms are *less* profitable than the other groups in terms of return on assets (RoA). We furthermore see that large firms ($\geq$ 250 employees) make up 0.6 percent of the firm-years in the Business Registry, 7 percent of the firm-years related to firms with patent applications and 3 percent of the firm-years related to firms with trademarks. Similarly, medium sized firms (20-250 employees) make up 3 percent of the firm-years in the Business Registry and 12 percent of the firm-years by firms with IPR (patents, trademarks or designs). Large and medium-sized firms thus have more IPR relative to their numbers. It is, of course, impossible to infer from these numbers the degree to which firm-growth leads to IPR filings versus the degree to which IPRs lead to firm-growth.

4 Empirical model

Our model assesses the impact of all forms of R&D support in Norway on the innovation rate of Norwegian firms. The main challenge is the endogenous selection into support programs due to unobserved or omitted variables affecting the outcome, known as confounding factors. This section introduces a new approach to address this challenge using our comprehensive data set described in Section 3.

Table 2: **Sample and descriptive statistics for the main variables in the business population**

Sample characteristics	All firms	Firms w. IPR	Patenting firms	Tradm. firms	IPR bundle
No. of firms	400,792	9,884	1,800	8,723	639
No. of treated firms[1]	17,821	3,973	1,382	3,147	556
No. of treatment-years[2]	85,987	33,220	14,764	26,446	7,990
Firm-years with INR support	31,629	9,934	4,193	7,979	2,238
Firm-years with RC support	12,880	7,333	4,464	5,611	2,742
Firm-years with SKF support	57,636	25,505	11,859	20,231	6,585
Total (NOK mill.) support	118,997	70,647	42,633	56,067	29,385
Share firm-age ≤ 3 (%)[3]	22	16	14	16	13
Share <50 empl. (%)[4]	66	57	51	56	48
Total IN support	30,321	14,158	7,951	11,139	4,931
Share firm-age ≤ 3 (%)	34	25	22	24	18
Share <50 empl. (%)	79	69	62	67	56
Total RC support	44,694	32,624	22,942	25,901	16,477
Share firm-age ≤ 3 (%)	17	13	11	14	12
Share <50 empl. (%)	46	42	39	41	38
Total SKF support	43,981	23,641	11,739	19,025	7,764
Share firm-age ≤ 3 (%)	19	14	13	14	11
Share <50 empl. (%)	77	71	68	69	64
Firm-year characteristics	mean (med.)	mean (med.)	mean (med.)	mean (med.)	mean (med.)
No. of employees	14.0 (4.0)	55.4 (9.0)	93.1 (12.0)	55.0 (9.0)	126.7 (18.0)
Return on assets (RoA)[5]	.061 (.034)	.060 (.056)	.013 (.026)	.067 (.061)	.018 (.042)
Firm age	11.8 (7.0)	14.9 (11)	15.0 (11)	15.1 (12.0)	17.0 (13)
Share firm-age ≤ 3 (%)	29	17	18	17	15
Share <5 empl. (%)	54	32	30	32	23
Share 5-49 empl. (%)	42	52	45	53	46
Share 50-250 empl. (%)	3.1	12	18	12	22
Share > 250 empl. (%)	0.6	3.5	6.9	3.4	8.9
Patent[6]	.002 (0)	.046 (0)	.234 (0)	.028 (0)	.300 (0)
Trademark[7]	.007 (0)	.142 (0)	.104 (0)	.160 (0)	.238 (0)
Design[8]	.0005 (0)	.011 (0)	.023 (0)	.009 (0)	.052 (0)

The table reports key variables at firm-year level during 2002-2021 in the Business Register (all Norwegian limited liability firms). IPR bundle refers to firms with patents in addition to one or both other types of IPR (trademark or designs). Nominal values in fixed 2021 prices. Notes: [1] Firms with support. [2] One firm-year with support. [3] Share of support given to firms $\leq$ 3 years old. [4] Share of support given to firms with $<$ 50 employees. [5] Returns on assets. [6] Dummy of at least one published patent application. [7] Dummy of at least one trademark filing. [8] Dummy of at least one design filing.

A popular method for overcoming the endogeneity problem is to apply a regression discontinuity design. For example, earlier studies of the Norwegian tax credit scheme (SKF) 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, they overlook that firms may apply for funding from several policy instruments (in addition to SKF) or apply many times, thus ignoring the multidimensional and staggered nature of treatment. Moreover, they do not consider the intensity of treatment, such as the amount or duration of support, which are important to our analysis.

Another popular approach is the quasi-experimental design, where treated firms are matched with a control group based on pre-treatment characteristics (x). The key identifying assumption is unconfoundedness: given x, treatment can be considered as if it is randomly assigned (see Rubin, 1990). This can involve propensity score matching, where treated units are matched with non-treated ones with the same probability of treatment. However, with multiple treatments, this strategy may not balance x in the matched sample. While this problem can be addressed by matching on x directly, new problems are introduced when the dimension of x is high, or even moderate.[17] In Nilsen et al. (2020), for example, the resulting matched sample included just over half the treated firms, with only six variables in x.

A common challenge with quasi-experimental approaches is the need for a high-dimensional x-vector to achieve unconfoundedness, if possible at all. To address this, we employ machine learning-based econometric techniques, specifically adapting the causal inference framework developed by Belloni et al. (2016) and Chernozhukov et al. (2018). This framework assumes a high-dimensional vector of confounding factors, which is approximated by sparse variable selection using the Lasso (see Hastie et al. (2017)). Lasso minimizes a negative log-likelihood plus a penalty term related to the sum of the absolute values of the coefficients. The number of control variables included depends on the weight given to the Lasso penalty term; higher weights result in more coefficients being estimated to be exactly zero.

For causal inference, even small mis-specifications of the control function can lead to significant bias. To make the inference robust to variable selection errors, Belloni et al. (2016) combines sparse model selection with a method of orthogonalization with roots in classical statistics, known as "immunization" (see Neyman, 1959).

4.1 Outcome and treatment variables

The *outcome* variable, $P_{i,[T,T+n)}$, is the total number of IPR applications of the given type (patents or trademarks) or a dummy of patent application in combination with trademark or design ("IPR boundle") in the time interval $[T,T+n)$, where T is an arbitrary calendar year, n is a fixed interval width (such as 3 or 5 years), and i refers to the firm. The vector $W_i = (T_i, D_i, S_i)$ characterises the *treatment*, where T_i is the first

[17] Exact coarsened matching can be used, where firms are stratified into cells based on a discretisation of x. Treated firms are then randomly matched to non-treated firms within each cell. The challenge is that as the dimension of x increases, more and more of the (non-empty) cells will contain only treated or non-treated firms, in which case the former cannot be matched.

year of support for firm i. Furthermore, $D_i \in \{1,..,n\}$ is the number of years with support in $[T_i, T_i+n)$ and $S_i = (S_{i,SKF}, S_{i,RC}, S_{i,INR})$ is the vector containing the total amount of support from the tax credit program (SKF), Research Council (RC), or Innovation Norway or Regional programs (INR) in the interval $[T_i, T_i+n)$. In the case of the "never-treated", $T_i = \infty$ ("never") and we set $W_i = 0$.

To denote number of IPR applications as a function of *potential* treatment, $W = (T, D, S)$, we write $P_{i,[T,T+n)}(W)$. Then for a treated firm i, $P_{i,[T_i,T_i+n)} = P_{i,[T_i,T_i+n)}(W_i)$. That is, the treated outcome is the observed one. For a firm with $T_i > T+n$ (possibly $T_i = \infty$), we assume $P_{i,[T,T+n)} = P_{i,[T,T+n)}(0)$, i.e. excluding the possibility that any future (possibly unobserved) treatment assignment affects the current outcome.

We summarize the treatment by two key concepts: *support dose*, defined as the total amount of support from all instruments combined:

$$\overline{S} = S_{SKF} + S_{RC} + S_{INR}$$

and the *main policy instrument*, defined as the largest source of support:

$$J = \underset{j \in \{SKF, RC, INR\}}{\arg\max} (S_j)$$

The usefulness of the concept of main policy instrument stems from the fact that there tends to be one dominant source of funding when research projects receive public funding from several sources (see Nilsen et al., 2020). First, firms that obtain direct support (RC or INR), generally also obtain tax credits (SKF) – but not the opposite. Moreover, if the main source of support is RC, the firm seldom obtains support from INR, and vice versa. This hierarchical structure is due to the fact that SKF is right-based, whereas there is fierce competition for research or innovation grants.

4.2 Treatment effects

To introduce basic concepts and notation, we will first consider a simplified model for the treatment effects where these are assumed to be captured by dummy variable coefficients, s_{dj} , i.e. only depending on the discrete properties of treatment: number of years with support (d) and the main policy instrument (j). In Section 4.3 we will make this specification substantially more flexible by adapting a discrete-continuous dose response framework, where treatment effects are a *function* of the amount of support received. For now we assume a simple count data model:

$$P_{i,[T,T+n)} = \exp(\sum_{dj} s_{dj} y_{iT}(d,j) + \beta x_{iT}) + u_{iT} \tag{1}$$

where $y_{iT}(d,j)$ is a dummy of a specific discrete treatment:

$$y_{iT}(d,j) = \begin{cases} 1 & \text{if } (T_i, D_i, J_i) = (T, d, j) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

βx_{iT} is the control function with row vector of (nuisance) parameters β, and u_{iT} is the (implied) mean zero error term.

The main condition for identification is that the vector of control varibales, x_{iT}, consists of a sufficient number of variables to satisfy un-confoundedness (Rubin, 1990):

$$W_i \perp P_{i,[T,T+n)}(W)|x_{iT} \text{ for all } \textit{potential} \text{ treatments } W.$$

Those who are selected into a particular treatment (either by self-selection or after winning a competiton for funding) may have systematically different non-treated outcomes than the non-treated, which could be a a source of bias when making inference about causal effects of treatment. The condition of unconfoundedness addresses this concern by requiring that the realized treatment, W_i, must be independent of the potential outcomes, $P_{i,[T,T+n)}(W)$ – for all possible W – conditional on the control variables, x_{iT}.

If we were to estimate the above model as a Poisson (or other count data) regression model, with $P_{i,[T,T+n)}$ as the dependent variable, the causal effects would be identified solely by functional form assumptions. Since y_{iT} and x_{iT} are likely to be highly correlated, any mis-specifications could turn up as a spurious treatment effect. In practice, the control function is unknown and the number of control variables may have to be very large in order for un-confoundedness to hold.

4.3 Dose response function

In a substantial generalization of the above model, we replace s_{dj} with a *dose response* function:

$$s_{dj}(\overline{S},\alpha_{dj}) = a_{dj} + b_{dj}\ln(\overline{S}) \tag{3}$$

where $\alpha_{dj} = (a_{dj}, b_{dj})$ are the parameters to be estimated. Equation (3) introduces a continuous variable in addition to the discrete treatment characteristics, duration and main source of support: the support dose, $\overline{S}$. The dose response function is scale invariant in the sense that $s_{dj}(k\overline{S},\alpha_{dj}) = b_{dj}\ln k + s_{dj}(\overline{S},\alpha_{dj})$. Thus it does not matter what scale is used to measure $\overline{S}$.

The support dose framework was first used in the context of public R&D support by Baum and Cerulli (2016) and Hottenrott and Lawson (2017) and generalized to a multivariate setting by Nilsen et al. (2020). To avoid further endogeneity issues, we have to assume that the realized support dose, which we denote $\overline{S}_i$, is randomly distributed conditional on $(D_i, J_i, T_i, x_{iT_i})$. Nilsen et al. (2020) give detailed arguments of why this condition is plausible in the Norwegian context.

The above functional form assumes that given the main policy instrument, the impact of the support depends both on the amount and duration of support. In the interest of sparsity *and* interpretability, we will consider (testable) parameter restrictions in our empirical application. First, duration of support may have no impact of outcomes given the amount of support, which implies the restriction: $\alpha_{dj} = (a_{1j}, b_{1j})$ for all d. The next natural restriction is that the effect of support does not depend on the policy instrument (j), which amounts to: $\alpha_{dj} = (a_{d1}, b_{d1})$ for all j. The effect might even be zero, which would amount to: $\alpha_{dj} = (0,0)$.

The above framework allows us to define additionality (*Addit*) of support dose, i.e. the number of additional IPR generated by a unit increase in $\overline{S}$, as follows:

$$Addit = \frac{\partial E(P_{i,[T,T+n)}(W_i))}{\partial \overline{S}_i} = \frac{b_{dj}}{\overline{S}_i} E(P_{i,[T,T+n)}(W_i)) \tag{4}$$

(assuming $y_{iT}(d,j) = 1$). Consequently, $1/Addit$ is the marginal public funding cost of IPR, i.e. the amount of public support dose required to generate – on average – one additional IPR of the given type.

4.4 Interpretations

Our dose response function can be interpreted in terms of elasticities of the expected number of IPR applications with respect to support dose, $\overline{S}$. Assuming $y_{iT}(d,j) = 1$:

$$\mathrm{El}_{\overline{S}} E(P_{i,[T,T+n)}(W)) = b_{dj}$$

To interpret this elasticity, the so-called CDM model (Crépon et al., 1998) is useful. In the innovation stage of the CDM model, assume an IPR production function:

$$\ln E(P_{i,[T,T+n)}) = \nu \ln(I_{iT} + \overline{S}_{iT}) + \beta x_{iT} \tag{5}$$

where ν is R&D elasticity, $I_{iT} > 0$ is internally funded R&D and $\overline{S}_{iT} = \sum_{dj} y_{iT}(d,j)\overline{S}$ is realized R&D support. Then, if $y_{iT}(d,j) = 1$:

$$\mathrm{El}_{\overline{S}} E(P_{i,[T,T+n)}) = \nu\left(\frac{\overline{S}_{iT}}{\overline{S}_{iT} + I_{iT}} + \frac{I_{iT}}{\overline{S}_{iT} + I_{iT}} \mathrm{El}_{\overline{S}} I_{iT}\right) = b^f_{dj}$$

This result suggest that b_{dj} is firm-specific (denoted b^f_{dj}) and would normally be increasing in the share of public R&D funding relative to total R&D. That is, if internally funded R&D increases *less* than one percent when support increases by one percent.[18] Building on this insight, we allow b_{dj} to depend on firms' pre-treatment characteristics (f) in the empirical section of this paper.

It is interesting to compare the general expression for *Addit* in Equation (4), with an expression for the marginal product (*MP*) of privately funded R&D derived from the structural Equation (5):

$$MP = \frac{\partial E(P_{i,[T,T+n)}(W_i))}{\partial I_{it}} = \frac{\nu I_{iT}}{\overline{S}_{iT} + I_{iT}} E(P_{i,[T,T+n)}(W_i)) \tag{6}$$

Under the highly desired property that $\mathrm{El}_{\overline{S}} I_{iT} \geq 0$, i.e. the support does not *crowd out* privately funded R&D, and setting $b_{dj} = b^f_{dj}$ in Equation (4): $Addit \geq MP$ (with equality if $\mathrm{El}_{\overline{S}} I_{iT} = 0$). Moreover, assuming

[18] It would be natural to think of this as input additionality being less than one, but input additionality is usually defined as the (NOK) increase in internally financed R&D when R&D support increases by one (NOK) – not in terms of percentage increase or elasticity.

the price of R&D is normalized to one (this is equivalent to deflating all revenue and cost components by the price index for R&D investments; see Cappelen et al. (2023): $MC = 1/MP$. Hence $MC \geq 1/Addit$. This results will be useful when interpreting *Addit* estimates in the empirical section.

5 Estimation

The estimation strategy consist of two stages. The first stage uses "double selection" to identify the *non-zero* components of β by Lasso-regressions, heavily penalizing complex models using a specific formula for the regularization parameter. Belloni et al. (2016) establish consistency results related to the double selection estimator under a technical sparsity condition, which intuitively means that the number of non-zero coefficients of β is small relative to the dimension of β. Since our dependent variables are count variables (corresponding to different types of IPR) and treatment is discrete-continuous, we adapt the generalized linear model version of double selection to accomodate logit and Poisson regressions, originally proposed by Belloni et al. (2016). We show that a key "immunity condition" is satisfied for this extension, meaning that inference about the causal parameters is robust to moderate variable selection mistakes.

First, we define a dummy variable indicating a non-treated (or "not-yet" treated) firm at T as:

$$y_{iT}(0) = \begin{cases} 1 & \text{if } T_i \geq T+n \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Next, we assume that the probability that $y_{iT}(d,j) = 1$, conditional on $y_{iT}(d,j) + y_{iT}(0) = 1$, is given by the logit probability $p(\theta_{dj}x_{iT}) = 1/(1+\exp(-\theta_{dj}x_{iT}))$. The conditional logit model is consistent with a multinomial probability model conditional on $y_{iT}(0) + \sum_{d,j} y_{iT}(d,j) = 1$.

5.1 Selection of estimation sample

The outcome $y_{iT}(0) = 1$ may be observed in adjacent years for the same firm, causing deterministic dependence between observations arising from the same year being included in overlapping n-year intervals. This undermines the possibilities for statistical inference. As a remedy, we select the estimation sample by *under-sampling* the non-treated firm-years, taking advantage of the fact that there is a huge number of non-treated firm years relative to treated ones. The under-sampled version of $y_{iT}(d,j)$ is the random variable $y'_{iT}(d,j)$ defined by:

$$y'_{iT}(d,j) = \begin{cases} 1 & \text{if } y_{iT}(d,j) = 1 \\ 0 & \text{if } y_{iT}(0) = 1 \text{ and } (i,T) \text{ is randomly sampled} \end{cases}$$

The distribution of $y'_{iT}(d,j)$ refers to the sub-population:

$$\mathbb{Y}(d,j) = \{(i,T) : y'_{iT}(d,j) \in \{0,1\}\}$$

which contains a random sub-set of all firm-years with $y_{iT}(0) = 1$ (the controls) and all firm-years with $y_{iT}(d,j) = 1$ (the treated).

More specifically, our under-sampling scheme is designed such that: (i) A sampled firm-year with $y_{iT} = 0$ is allocated to *one* risk set, $\mathbb{Y}(d,j)$. This is to avoid double counting of the same firm-year in the estimation sample. (ii) Only one T with $y_{i,T} = 0$ can be sampled per firm (i). This is to avoid non-tractable serial correlations of the type mentioned above. (iii) A constant fraction, ν, of all firms with $y_{iT}(0) = 1$ is included in $\mathbb{Y}(d,j)$ in each year, T. Thus, the non-treated firms in $\mathbb{Y}(d,j)$ can be considered a randomly selected "control group" to the firms with $y_{iT}(d,j) = 1$. Of course, they may have a very different covariate distribution than the treated firms in $\mathbb{Y}(d,j)$, as the sampling scheme involves no (covariate) matching.

Under the above sampling scheme, let p'_{dj} and p_{dj} denote the conditional probability that $y'_{iT}(d,j) = 1$ and $y_{iT}(d,j) = 1$, respectively . Then

$$p'_{dj}/(1-p'_{dj}) = \nu^{-1}p_{dj}/(1-p_{dj}) = \nu^{-1}\exp(\theta_{dj}x) = \exp(\theta_{dj}x - \ln\nu)$$

which shows that under-sampling only affects the intercept of the logit model. The potential loss of information by under-sampling is compensated by the final sample consisting of independent firm-years. Moreover, since there is a huge set of non-treated relative to treated firm-years, the loss of information should be small. The benefits are obvious: well-known statistical inference theory may be applied in a novel setting.

5.2 GMM

The first stage of the estimation selects the control variables by means of Lasso regressions and, furthermore, yields post selection estimates $(\widetilde{\beta}, \widetilde{\theta}_{dj}, \widetilde{\alpha}_{dj})$; see Appendix A. In the second stage, the parameters related to the causal effect of the support dose (α_{dj}) are re-estimated by means of GMM to "immunize" the estimator to errors in the nuisance parameters. This stage is detailed in the following:

GMM Estimation

Define logit-residuals:

$$v_{dj}(x_{iT};\theta_{dj}) = y_{iT}(d,j) - p_{dj}(\theta_{dj}x_{iT}) \tag{8}$$

and Poisson-residuals

$$u_{dj}(x_{iT};\alpha_{dj},\beta) = P_{i,[T,T+n)} - \exp(s_{dj}(\overline{S}_i;\alpha_{dj})y_{iT}(d,j) + \beta x_{iT}) \tag{9}$$

and let $\overline{s}(d,j)$ denote the average of $\ln(\overline{S}_i)$ in the collection of firm-years with $y_{iT}(d,j) = 1$. The GMM estimator $\widehat{\alpha}_{dj}$ is obtained by solving:

$$Q_{dj}(\alpha_{dj};\widetilde{\beta},\widetilde{\theta}) \equiv \sum_{(i,T)\in\mathbb{Y}(d,j)} u_{dj}(x_{iT};\alpha_{dj},\widetilde{\beta})v_{dj}(x_{iT};\widetilde{\theta}_{dj}) = 0 \tag{10}$$

and

$$R_{dj}(\alpha_{dj};\widetilde{\beta}) \equiv \sum_{(i,T)\in\mathbb{Y}(d,j)} y_{iT}(d,j)u_{dj}(x_{iT};\alpha_{dj},\widetilde{\beta})\left(\ln(\overline{S}_i)-\overline{s}(d,j)\right)=0 \tag{11}$$

with respect to α_{dj}, where $\widetilde{\beta}$ and $\widetilde{\theta}_{dj}$ are the post selection estimates of β and θ_{dj} defined in Appendix A.

We make the following observations. First, the basis for Equations (10)-(11) are the theoretical moment conditions $E\left[u_{iT}v_{dj}(x_{iT};\theta^0_{dj})\right]=0$ and $E\left[y_{iT}(d,j)u_{iT}(\ln(\overline{S}_i)-\overline{s}(d,j))\right]=0$. In fact, these orthogonality condition are identical to the first order conditions with respect to α_{dj} in the double selection procedure in Appendix A (Step 3), except that $y_{iT}(d,j)$ is replaced with $v_{dj}(x_{iT};\widetilde{\theta}_{dj}) = y_{iT}(d,j)-p_{dj}(\widetilde{\theta}_{dj}x_{iT})$ in (10) and $\ln(\overline{S}_i)$ with $\ln(\overline{S}_i)-\overline{s}(d,j)$ in (11). This centering is key to the immunization discussed above and causes the GMM estimate, $\widehat{\alpha}_{dj}$, to differ from the post selection estimate, $\widetilde{\alpha}_{dj}$ (see Belloni et al., 2016, for an analogous result in the case of a continuous treatment variable only). Second, Equations (10)-(11) exactly identify $\widehat{\alpha}_{dj}$, which makes the GMM estimator (asymptotically) independent of the GMM weight matrix (see Hansen and Lee, 2021). Third, double selection never allows us to make inference about the nuisance parameters. Even in large samples, variables with non-zero β coefficients may not be included in the double selection stage. Nevertheless, the immunity condition by Belloni et al. (2016), adapted to our setting in Proposition 1, says that $\widehat{\alpha}_{dj}$ is insensitive to first-order errors in the nuisance parameters.

Proposition 1. *The GMM estimator $\widehat{\alpha}_{dj}$ is first-order immune to errors in the nuisance parameters in the sense that:*

$$\frac{\partial}{\partial\beta}E\left\{Q_{dj}(\alpha^0_{dj};\beta,\theta^0)\right\}\big|_{\beta=\beta^0}=0,\ \frac{\partial}{\partial\theta}E\left\{Q_{dj}(\alpha^0_{dj};\beta^0,\theta)\big|_{\theta=\theta^0}\right\}=0,\ \frac{\partial}{\partial\beta}E\left\{R_{dj}(\alpha^0_{dj};\beta)\big|_{\beta=\beta^0}\right\}=0 \tag{12}$$

Proof: See Appendix B.

5.3 Control variables

Our procedure is based on a vector of control variables variables, x_{iT}, which characterizes the firm prior to (potentially) receiving treatment. Nilsen et al. (2020) identified five critical control variables: NACE industry, firm-age, number of employees, R&D expenditure and (a dummy of having) IPR. Based on their findings, we start constructing the universe of possible x_{iT} by defining a vector of categorical variables, cat, as follows:

$$cat = (ind, age, empl, rnd, pat, trm, des)$$

where *ind* is 2-digit NACE industry, *age* is an ordinal variable referring to age (0–3, 4–9, or >9 years), *empl* is an ordinal variable referring to number of employees (<5, 5–49, 50-249, >250) and *rnd* represents *R&D-status* on an ordinal scale: $rnd=1$ if the firm was *not* R&D active (including obtained R&D support or filed patent applications) in any of the five preceding years; $rnd=2$ if the firm was R&D active with average R&D expenditure below the median; and $rnd = 3$ otherwise (i.e., average R&D expenditure above the median). Finally, pat, trm and des are ordinal variables valued 1 if the firm had zero patent, trademark or design filing since 1995, respectively; 2 if the firm had one patent, trademark or design filing since 1995, respectively, and 3 otherwise (i.e., more than one filing). Our vector of potential control variables include *all possible* 1. order interactions between the components of cat, such as for example ind (main effect) and $ind \times age$ (1. order interaction).

We also include a set of continuous variables: number of employees, total assets, firm age, number of lagged patents, number of lagged trademarks, capital intensity, labour productivity and shares of employees with upper secondary education (13-17 years) and academic education ($\geq$ 18 years). The total number of components of x_{iT} is of a very high magnitude. Only a very small subset of these are selected by the Lasso and included in the final GMM estimation (see Tables 8-9 in the Appendix).

6 Results

Our analyses use patent and trademark counts as the main dependent variables in combination with the Lasso-based control variable selection framework outlined in Section 5. In complementary analyses we use "IPR bundle" as the dependent variable, i.e. a dummy variable of having a published patent application and *in addition* at least one trademark or design filing in the same $n-$year interval.

Table 3 presents basic statistics for the final estimation sample. Number of patents, trademarks, and support dose refer to 3-year intervals ($n = 3$). Thus number of IPR refers to the *sum* of filings over an interval, recorded by application date, whereas *support dose* refers to the sum of R&D support over the same interval (in NOK million fixed 2021 prices). Absent missing variables, a firm (i) that obtained *first-time* support in year $T_i \in [2002, 2019]$ is represented in Table 3 by variables measured over the interval $[T_i, T_i + 3)$. Firms labeled "controls" are randomly sampled and their characteristics are similarly measured over 3-year intervals $[T, T + 3)$, where T is randomly selected for each firm conditional on $y_{iT}(0) = 1)$ (see Section 5.1 for details).

There are four main features of Table 3. First, firms that are more than 3 years old at the beginning of the time interval ("incumbent firms") and have some R&D experience during the preceding 5 years ("R&D-active") have much higher probability of having IPR filings than other firms. Second, R&D-active firms that obtain support mainly from RC or SKF have almost twice as high probability of patenting than any other group in Table 3. Third, the mean number of patents and trademarks among the controls without previous R&D experience (about 0.002 and 0.03, respectively) are much lower than for the corresponding treated firms. The difference is especially striking with regard to patent applications. Although the control function corrects for differences in confounding factors in the estimation, there is a risk that "selection on unobservables" could also cause imbalances, which means that estimation results with regard to this group should be interpreted carefully. Fourth, RC funding tends to be given to fewer firms, but in higher amounts per firm, compared to SKF and INR funding. In fact, the number of firms with RC as the main

Table 3: Characteristics of firms in final estimation sample with respect to mean (median) support dose and mean number of IPR applications in 3-year intervals. By main policy instrument, R&D experience and firm-age

Main instr.	R&D-active	Age-group	Support dose	Patents	Tradem.	Firms
INR	Yes	Incumbent	1.60 (0.56)	0.19	0.23	175
	No	Incumbent	0.95 (0.41)	0.02	0.08	2,720
	No	Startup	1.17 (0.50)	0.08	0.14	2,550
RC	Yes	Incumbent	5.47 (2.67)	0.31	0.29	76
	No	Incumbent	2.21 (0.84)	0.06	0.10	315
	No	Startup	4.48 (2.08)	0.14	0.25	228
SKF	Yes	Incumbent	1.82 (1.29)	0.35	0.26	683
	No	Incumbent	1.31 (0.81)	0.03	0.12	4,109
	No	Startup	1.59 (1.03)	0.09	0.16	2,112
Controls	Yes	Incumbent	–	0.15	0.32	287
	No	Incumbent	–	0.001	0.029	29,124
	No	Startup	–	0.002	0.027	6,304

Startup firms are $\leq$ 3 years old at the start of the 3-year interval. R&D-active firms are incumbent firms with some R&D activity (including IPR filings) in the preceding five years. Mean and median (in parenthesis) support dose is the sum of total R&D support over all instruments (INR, RC and SKF) and all years in the interval $[T_i, T_i + 3)$, classified by main source of support (main instrument). In NOK million (fixed 2021 prices).

policy instrument is roughly 1/10 to that of SKF. In contrast, a higher share of INR funding is given in smaller amounts even compared to SKF funding. These patterns were already noted in relation to Figure 3.

We proceeded by first testing the following restrictions: $b_{jd} = b_j$ and $a_{jd} = a_j$, i.e., the scaling of the dose does not depend on number of years with support (d). Second, we tested: $a_j = a$, i.e., the dose scaling factor is independent of both policy instrument and number of years with support. These restrictions were clearly not rejected and therefore imposed in the final estimation to simplify comparisons across policy instruments. On the other hand, we allow heterogeneity in support dose elasticities along two dimensions with regard to firm characteristics (f) at the time of treatment assignment: (i) R&D-starters vs. R&D-active, and (ii) startup vs. incumbent firms. Moreover, we use the notation b_j^f to denote the elasticity – our interest parameter – as a function of main policy instrument (j) and firms' pre-treatment characteristics (f).

6.1 Dose response elasticities

The estimated dose response elasticities presented in Table 4 reveal a distinct pattern with respect to patenting: the estimates for R&D-active firms (i.e., *prior* to obtain first-time support) are uniformly smaller and less significant than for R&D-starters. In the former group, the estimated elasticities vary from 0.10 (RC) to 0.14 (SKF), and is either insignificant at the 95 percent level (RC) or just significant (INR and SKF). In contrast, R&D-starters – in particular startup firms – exhibit highly significant estimates, varying from 0.45 (RC) to 0.52 (INR), with z-values exceeding 5. These results closely align with the finding of Nilsen et al. (2020) that output additionality with regard to *employment* and *value added* growth were insignificant for R&D-active firms, but highly significant for R&D-starters. Note that the higher estimates for R&D-starters compared to R&D-active firms do not mean that the former are more efficient in converting a given amount of R&D investment into innovation outcomes. As shown in Section 4.3, a higher elasticity follows *cet. par.* from the subsidy making up a larger share of total R&D for R&D-starters compared to R&D-active firms.

We observe a similar pattern for trademarks as patents: the estimated dose response elasticities are higher for R&D-starters compared to R&D-active firms, with insignificant or just significant estimates in the latter group and highly significantly in the former. The range of the estimated elasticities is slightly narrower for trademarks compared to patents: For R&D-active firms, it varies from 0.10 (RC) to 0.17 (INR), with z-values between 1.0 and 2.7. For R&D-starters, the estimated support dose elasticity varies from 0.28 (RC) to 0.37 (INR), with z-values exceeding 4.9. Overall, the impact of BERD support is smaller on trademark counts than patent counts, but always highly significant at the extensive margin, i.e. for firms without prior R&D experience.

Regarding "IPR bundles", we observe a similar pattern as for patents, with estimated elasticities in the range of 0.31 (RC) to 0.52 (SKF). The corresponding z-values are in the range of 1.7–4.0, with weakly significant or insignificant estimates found for R&D-active firms. From the lower part of Table 4, we see that combinations of different IPR are common. For example, the 721 patent applications in the estimation sample coincides (in the same 3-year interval) with 218 trademarks and 90 designs. Similarly, the 2,408 trademarks coincides with 215 patents and 128 designs.

An interesting aspect of Table 4 is that the source of funding does not seem to matter for the estimates. In particular, the estimates for tax credits (SKF) are statistically indistinguishable from the estimates for direct grants (INR or RC). Thus there seems to be no value added from "picking winners" through funding competitions compared to simply having a right based tax credit program.

Table 5 shows the importance of double vs. single selection of control variables, i.e. the impact on the elasticity estimates of *not* including (in Table 5) control variables specifically predicting treatment – only of IPR counts. Although the overall pattern of the results with single selection are of similar magnitude as the estimates with double selection (in Table 4), there are some striking differences. First, with single selection, the estimates for R&D-active firms becomes uniformly higher and the estimates for R&D-starters

becomes uniformly lower. Furthermore, the estimates across firm characteristics (for given main instrument) are very similar with single selection – with always overlapping confidence intervals. These results illustrate the key role of the two-step procedure in identifying confounding factors, i.e. the importance of including both (Lasso-selected) predictors of treatment *and* of IPR outcomes as control variables (see Appendix A for details about single vs. double selection).

Tables (8) and (9) in the Appendix show the estimates for the included control variables after double selection in the case of patent and trademark counts as dependent variables, respectively. The most important predictors of IPR counts are the measures of previous IPR and R&D activities, both alone and in interaction with other variables such as firm size and firm age.

In summary, our findings support and elaborate earlier work that fiscal stimulus tends to have greatest impact on previously non-innovative firms or firms without previous R&D experience. A significant impact of support measures, alone or in combination, is found on the extensive rather than intensive margin.

6.2 Temporal intervals

We noted in relation to Table 4 that the source of funding does not matter for the estimates. In particular, the estimates for tax credits (SKF) are indistinguishable from the estimates for direct grants. One possible explanation could be that grants are given in an early phase of a project and/or to more complex projects, so that it takes longer time to realize the innovations. To address this issue, we investigate in Table 6 the effect of widening the time interval during which we measure IPR counts (and BERD support) from $n = 3$ to $n = 5$.

The results in Table 6 are practically the same as in Table 4. For example, all point estimates in Table 6 are included in the corresponding confidence intervals in Table 4, and vice versa. The most notable difference between Table 6 and Table 4 is that, with $n = 5$, a much larger share of the patent counts represent an IPR bundle (532 of 860), compared to $n = 3$ (291 of 721). The estimates for IPR bundle in Table 6 are also much closer to the estimates of patent counts – and generally much more significant – compared to Table 4.

We noted in relation to Figure 5 that patents are much more common relative to trademarks in certain manufacturing industries, whereas trademarks are relatively more common than patents in services. To investigate industry specificity we split the sample in two main sectors: Manufacturing and Services and estimate models for each sector separately (leaving out Primary industries; Mining, oil and gas extraction, and Power production, waste and recycling in this part of the analyses). The estimated elasticities for Manufacturing are shown in Appendix Table 10 for $n = 3$ and Appendix Table 11 for $n = 5$. The estimates are generally less significant, which can be explained by the much smaller sample. In particular, most estimates for RC are insignificant or even negative when $n = 3$. When $n = 5$, we recognize the pattern of Table 6 also in Appendix Table 11, but less distinctly. First, there is no significant differences in elasticities across firm characteristics (f) for given main instrument (j). The estimates for both patents and trademarks are mostly still significant for R&D-starters, but lower, and less significant compared to the main results. Second, most estimates for trademarks are smaller than for patents, except for some anomalous negative estimates with regard to patent counts for RC.

Thus, while the results for Manufacturing are noticeably weaker and more ambiguous than for all industries combined, the results for Services in Appendix Table 12 ($n = 3$) and Appendix Table 13 ($n = 5$) confirm or even strengthen the results of Tables 4 and 6. With regard to patents, the estimates for R&D-starters are significantly higher than for R&D-active firms, which are mostly insignificant or weakly significant. For trademarks, there are few differences between Tables 4 and 6, on the one hand, and the corresponding results for Services (Appendix Tables 12 -13). This is not unexpected, given that Services account for nearly 75 percent of all trademark filings in the estimation sample, compared to about 50 percent of all (published) patent applications.

Although patents are relatively rare in Services, the impact of R&D support on the propensity to patent is at least as strong in Services as in Manufacturing – in fact, the estimated elasticities are higher in Services. This result is interesting in view of the findings of Nilsen and Raknerud (2024): while first-time patenting firms in general are found to increase their economic activity just before and after applying for a patent, as measured by R&D, employment, total assets and value added, the effects are stronger and more long lasting in Services than in Manufacturing.

6.3 Additionality

Table 7 reports additionality estimates by main policy instrument (j) and firm characteristics (f). That is, the expected number of additional IPR generated by NOK 1 million increased support.[19] Averaging over policy instruments (j) and time interval widths (n), the highest and most significant additionality estimates, regardless of IPR type, are found for startups: 0.03 for patents – with 95% confidence interval: [.01,.05] – and 0.025 for trademarks – with confidence interval: [.00,.04]. These results indicate highly significant output additionality estimates for patents and weakly significant estimates for trademarks (signifiant at the 90% level, but not 95%). Averaging across firm types, the mean additionality estimate becomes 0.02 for both patents trademarks – with 95% confidence interval equal to [.01,.05] and [.00,.04], respectively. The differences in estimates and significance levels are thus less clear for additionality than for dose response elasticities, especially the distinction between R&D-active vs. R&D-starters (regardless of firm age). The reason is that R&D-active firms have more IPR relative to R&D support compared to R&D-starters, but lower dose response elasticities (cf. Equation (7)). Comparing additionality estimates across firm types, we see that the estimates for startups are always highly significant, whereas for the other firm types they are often not significant at the 95% level (i.e., the confidence interval includes zero).

[19] Using Equation (4) to estimate average *Addit* in a group of firms, say $G(j,f)$, we replace $b_j^f \mathrm{E}(P_{i,[T_i,T_i+n)]})/\overline{S}_i$ with $\widehat{b}_j^f \overline{P}_j^f / \overline{S}_j^f$, where $\overline{P}_j^f = \sum_{i \in G(j,f)} P_{i,[T_i,T_i+n)]}/N_j^f$ and N_j^f is the number of firms in $G(j,f)$ (see the last column of Table 3 for a listing of number of firms by group). Similarly, $\overline{S}_j^f$ is the mean support dose $\overline{S}_i$ over $i \in G(j,f)$. Using a standard variance formula involving the Poisson distribution with $\overline{S}_j^f$ fixed: $\mathrm{Var}(\widehat{b}_j^f \overline{P}_j^f / \overline{S}_j^f) \approx \mathrm{Var}(\widehat{b}_j^f)((\overline{P}_j^f)^2 + \overline{P}_j^f / N_j^f)/(\overline{S}_j^f)^2$.

The same public funding could lead to either a patent, a trademark, a design, or a combination of different IPR types. Thus, the additionality with respect to (the sum of) *all* IPR is the sum of *Addit* for the different types. These results are shown in the last six columns of Table 7 ("Total IPR count"). The estimates are based on count data models with total IPR count as the dependent variable (sum of patents, trademarks and designs). The point estimate for startups, averaging across policy instruments and time interval widths, is 0.05 – with 95% confidence interval: [0.02,0.07]. Averaging across all firms types, the point estimate becomes 0.03 – with confidence interval: [0.01,0.06]. Again, we see that the effects are stronger and more significant for startups than for incumbents (both R&D-active and R&D-inactive).

As explained in Section 4, the marginal funding cost of an IPR is $1/Addit$, i.e. the public support required on average to generate an additional IPR. Thus the lower and upper limit of the 95% confidence interval for the estimated marginal funding cost of an IPR, regardless of type and instrument, is NOK 14 ($= 1/0.07$) and 50 ($= 1/0.02$) million for startups, and NOK 17 ($= 1/0.06$) and 100 ($= 1/0.01$) million across all firm types.

IPR filings may not be a relevant outcome measure for all public R&D support. In fact, the descriptive statistics of Table 2 indicate that they are so for about 2/3 of it. Assume, conversely, that 1/3 of the support is *not* an investment in IPR development, but has other objectives. Then *Addit* is increased by a factor of 3/2 on average (i.e., by reducing $\overline{S}_i$ to $2\overline{S}_i/3$ in Equation (7)). Consequently, the confidence interval for the marginal (public funding) cost of an IPR is reduced to between NOK 10 and 33 million for startups and between 12 and 66 million across all firm types.

To put these figures in a context: data on *activated* R&D show that the sum of (activated) R&D divided by sum of IPR filings over 5-year time intervals $[T_i, T_i + 5)$ for all firms that obtained BERD support is NOK 7 million (as explained, T_i is the year of first-time support of firm i). Since R&D specifically aimed at IPR development are normally activated according to accounting rules,[20] NOK 7 million is a meaningful estimate of the average R&D investment cost of an IPR. Even if we add administrative and legal fees,[21] the normal cost of an IPR seems to be significantly lower than the public funding required to generate an additional one. Although, in theory, publicly funded projects could be more costly than the average project, this is not likely to be the case for tax credits (SKF), which do not discriminate between projects or firms. Although the results in Table 7 indicate higher additionality for SKF than RC (possibly reflecting lower MC; cf. the discussion in Section 4.4), the differences are within the margin of error (i.e., *cet. par.*, all the confidence intervals overlap across policy instruments). Thus, unless our additionality estimates are heavily downwards biased (in fact, we expect them to be upward biased for startups), our results suggest 'crowding out': public BERD funding partly replaces private funding. As a result, R&D support programs could be very costly to taxpayers, as they do not fully represent new investments, but substitute private funding.

Our data further indicate that the average market value of an IPR (net of all non-R&D costs) is a markup

[20] See https://verdtavite.kpmg.no/immaterielle-eiendeler.aspx (in Norwegian)

[21] The sum of *all* administrative fees related to application and renewal of an EPO patent over a period of 20 years is EUR 145,000 (NOK 1,8 mill). See https://www.epo.org/en/applying/fees/fees

over NOK 7 million – the average activated R&D investment per IPR – which is far below the lower bound of any of our confidence intervals for the (public) cost of funding an additional IPR. The markup should be moderate as there is no indication in our data that firms with IPR have higher returns on their investments than other firms; see Table (2). The public R&D funding must therefore generate societal value considerably above the market value of the innovations being funded to justify their current level and distributional profile.

Regardless of the magnitude of additionality of BERD support, we consistently estimate both *Addit* and support dose elasticities to be lower for R&D-active firms compared to R&D-starters, especially startups. Many estimates are not even significantly different from zero for R&D-active firms. As shown in Table 3, support obtained from RC is more concentrated in this group (78%), than support from SKF (62%) and INR (50%). The number of insignificant estimates increases further when estimates are obtained separately for Manufacturing and Services (see Appendix Tables 10-15). The estimates that remain significantly positive regardless of industry are all related to startups with SKF or INR as their main source of BERD support.

7 Conclusions and implications

Since introducing tax credits in 2002, Norway has provided approximately NOK 120 billion (EUR 12 billion) in total BERD support, both in the form of tax credits and direct support (grants). We examined the effect of this support on the innovative output of the Norwegian firms during this period. Our objective was to accurately assess the subsidy-induced effects of the full range of R&D subsidy programs over time, while addressing known empirical challenges to causal inference.

This paper makes several empirical contributions that consolidate and enrich the output additionality literature. We integrated a comprehensive set of firm-level data, covering hundreds of variables related to all support measures over the full time period. We extended the measurement of innovation to include trademarks and industrial designs, in addition to patents. Furthermore, we employed a two-stage empirical approach to address recognized challenges to causal inference identified in the literature.

While the data-integration step and the causal inference approach were necessarily complicated, our findings are more straightforward. They confirm earlier research while enriching our understanding of the effects of different R&D support mechanisms on different firm sub-populations. In terms of overall impact of public R&D support, our findings confirm that both direct subsidies and tax credits significantly increase innovation output as measured by intellectual property rights (IPR): both in terms of numbers of patent and trademark registrations, frequency of "IPR bundles" (patents, trademarks, and/or designs in combination), and total IPR counts . Our results show that the impact is more pronounced for patents compared to trademarks, but that the overall pattern of increased innovation output is consistent across all the different IPR-based measures. The general pattern is also observed both when IPR are aggregated over shorter (3 year) and longer (5 year) intervals, although effects vary within different firm sub-populations .

An important finding is that we find broadly similar results independently of the source of support (either direct or indirect).

Beyond that general picture, our study uncovers some important differences within these aggregate results. An important take-away is that our analysis demonstrates systematic differences between two types of recipient firms: those with prior innovative activity ('R&D -active') and those without ('R&D-starters') before obtaining support.

R&D-active firms are an important group consisting of a relatively limited number of firms that traditionally have been targeted for support. They are defined to be older than three years ("incumbent firms") and have previous R&D experience before obtaining support. These firms received approximately 60% of R&D support in Norway over the past two decades, and an even larger share of Research Council (RC) funding (80%). An important result of our analysis is that, despite receiving most of the support, the subsidy-induced innovation output for these firms is limited. We find weak or negligible levels of additionality measured over three years after obtaining first-time support, becoming only slightly more pronounced after five years for patents.

R&D-starters (either startups or incumbents) constitute a numerous and diverse group. These firms receive substantially less overall support compared to R&D-active firms. However, they show significant responses to both direct and indirect policy instruments across various outcomes. R&D-starters significantly contribute to the positive overall innovation output additionality, with particularly strong effects on patenting and IPR bundles, as well as notable effects on trademarks and total IPR counts.

The stark differences between the two groups of firms hold implications for government R&D support strategies. Although our study was meticulous about including comprehensive firm-level information to control for potential confounding factors, it is striking how little these factors contribute to our findings in and of themselves. When we control for firms' R&D experience and their IPR history, we find no evidence that other variables, such as firm-size, have a separate impact on the effect of the R&D-support schemes. For previously R&D-active firms, our results show that public support has low – even statistically insignificant – additionality. There are in other words diminishing returns to public R&D support on innovation output assessed in terms of patents and other IPR.

These findings help to qualify earlier results from Italy, the UK, and Norway. Here, our results suggest that R&D starters may be contributing disproportionately to output additionality. Our findings can meanwhile also provide a clarification for ambiguous results observed in earlier studies. We show that R&D support adds relatively little to IPR outcomes among R&D-active firms. The low level of additionality in this sub-population can help explain why earlier studies, such as Cappelen et al. (2012), found no significant effect of tax credits on patent counts. The earlier study focused on a sample of Norwegian respondents of the CIS survey, which consists disproportionally of research-active incumbent firms.

Our results have some potentially important policy implications. Off the top, our findings confirm that public investment to support business enterprise R&D does contribute to additional innovation output in the economy. There are thus seemingly good reasons to continue to support BERD. On the other hand, our low additionality estimates for R&D-active firms, suggest that public R&D funding may partly replace private funding, indicating 'crowding-out'. Governments should therefore be attentive to what makes a difference and what does not when designing the policy instruments.

A first important question is to what extent increasing the share of indirect vs. direct support affects the rate of innovation in the economy? Norway reflects the international tendency to adapt the channel for support. In short it has brought indirect support (tax credits) into line with direct support in recent years. This policy choice does, however, not appear to significantly affect the overall pattern of output additionality. The magnitude of support – not the source of it – is what matters to the rate of innovation. Thus, for example, low additionality for R&D-active firms is not associated with tax credits in particular.

A second important question is whether (or how) a larger population of firms without previous R&D activities could be induced to become innovative? This is relevant in view of our distinct result that R&D-starters respond more strongly to both direct and indirect support instruments than the (already) R&D-active firms.

A third issue is the interpretation of the effects of BERD support on R&D-active firms. As mentioned, we find that the output additionality of both direct support and tax credits for these firms is weak on aggregate. There are a range of interpretations of this finding that are beyond our scope and would require further study. On the one hand, there is the negative interpretation that chimes with a current concern in the Norwegian debate over public support. In short, the question is, again, whether BERD support is 'crowding out' existing activities of the R&D-active firms, and, as a result, do not fully represent new investments. This is a serious policy concern regarding the legitimacy of these programs and warrants more study.

There is also a set of more positive interpretations that are consistent with the intention of BERD support and with the overall positive findings in the literature. In short, the question is whether (or to what degree) R&D-active firms might be using public R&D support to adapt their innovation direction, take on more uncertain research projects, improve the quality of research output, and/or strengthen their role in innovation system? The hypothesis that BERD support promotes higher quality research outcomes may help to explain the substantial spillovers that the recent literature has traced back to BERD support (e.g. Myers and Lanahan, 2022).

The current study cannot definitively determine which of the interpretations best explains our, on aggregate, low additionality estimates. However, we have made several significant contributions to measuring and estimating the additionality of BERD support in general. One key contribution is our approach of combining IPR filings, both collectively and individually, to better and more broadly capture the innovation output from firms eligible for public R&D support. Nevertheless, a limitation remains: these innovation measures are still simple count variables. Innovation is a heterogeneous activity with numerous potential learning outcomes that may not be fully captured by such a measure. Future work could explore whether output additionality measures fail to capture innovation effects or if other factors counterbalance the apparent lack of economic efficiency. Potential unmeasured effects include quality improvements in innovation, shifts towards more beneficial innovation activities, or effects that strengthen innovation ecosystems. Additionally, BERD support might build redundant capacity, enhancing resilience amid uncertainty and crises. If so, these effects could offer significant social benefits.

Table 4: Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 3-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j). GMM estimates after Lasso-based double selection of control variables

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)											
	R&D-starter	Age-group	Patent count				Trademark count				IPR bundle (dummy)			
			Elast	z-value	95% CI		Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.13	2.14	0.01	0.26	0.17	2.74	0.05	0.30	0.34	2.07	0.02	0.67
	Yes	Incumbent	0.47	6.04	0.32	0.62	0.30	7.13	0.22	0.39	0.34	1.87	-0.02	0.70
	Yes	Startup	0.52	8.48	0.40	0.64	0.37	9.13	0.29	0.45	0.48	3.93	0.24	0.72
RC	No	Incumbent	0.10	1.79	-0.01	0.21	0.10	1.06	-0.09	0.29	-0.04	-0.14	-0.54	0.47
	Yes	Incumbent	0.47	5.59	0.30	0.63	0.28	4.90	0.17	0.39	0.40	2.23	0.05	0.75
	Yes	Startup	0.45	7.16	0.32	0.57	0.34	7.33	0.25	0.43	0.31	1.71	-0.05	0.67
SKF	No	Incumbent	0.14	2.35	0.02	0.25	0.14	2.69	0.04	0.24	0.30	2.09	0.02	0.57
	Yes	Incumbent	0.51	7.96	0.39	0.64	0.31	8.19	0.23	0.38	0.52	3.75	0.25	0.79
	Yes	Startup	0.49	8.33	0.38	0.61	0.33	8.61	0.26	0.41	0.45	3.37	0.19	0.71
No. of obs.			45,613				45,599				42,817			
Pseudo R^2			0.51				0.21				0.48			
Total patent counts[1]			721				215				219			
Total tradem. counts[2]			218				2,408				218			
Total design counts[3]			90				128				90			

Dependent variable is the number of applications of the corresponding IPR type in a time interval $[T, T+3)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same 3-year interval. GMM estimates after Lasso-based double selection of control variables. Robust standard errors (SE). Startups are ≤ 3 years old at the time of treatment assignment (other firms are incumbents). R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. Notes: [1] Number of patents in final estimation sample conditional on non-zero dependent variable [2] Number of trademarks in final estimation conditional on non-zero dependent variable. [3] Number of designs in final estimation sample conditional on non-zero dependent variable.

Table 5: GMM estimates after single selection of control variables. Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 3-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j).

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)											
	R&D-starter	Age-group	Patent count				Trademark count				IPR bundle (dummy)			
			Elast	z-value	95% CI		Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.45	7.15	0.32	0.57	0.26	4.61	0.15	0.36	0.36	3.37	0.15	0.57
	Yes	Incumbent	0.25	3.34	0.10	0.40	0.23	5.45	0.15	0.31	0.32	2.41	0.06	0.58
	Yes	Startup	0.43	6.75	0.31	0.56	0.29	7.02	0.21	0.31	0.44	4.73	0.26	0.62
RC	No	Incumbent	0.35	5.97	0.23	0.46	0.19	2.33	0.03	0.35	-0.04	-0.20	-0.47	0.38
	Yes	Incumbent	0.29	3.46	0.12	0.45	0.20	3.36	0.08	0.31	0.29	1.86	-0.02	0.59
	Yes	Startup	0.36	6.04	0.24	0.47	0.27	6.08	0.18	0.36	0.34	3.38	0.14	0.54
SKF	No	Incumbent	0.44	7.08	0.32	0.57	0.22	5.49	0.14	0.29	0.34	3.65	0.16	0.53
	Yes	Incumbent	0.30	5.05	0.18	0.42	0.21	5.68	0.14	0.29	0.42	4.36	0.23	0.61
	Yes	Startup	0.41	7.02	0.29	0.52	0.28	7.24	0.20	0.35	0.41	4.33	0.22	0.59

Dependent variable is the number of applications of the corresponding IPR type in a time interval $[T, T+3)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same 3-year interval. GMM estimates after single selection of control variables. Robust standard errors (SE). Startups are ≤ 3 years old at the time of treatment assignment (other firms are incumbents). R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters.

Table 6: Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 5-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j). GMM estimates after Lasso-based double selection of control variables

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)											
	R&D-starter	Age-group	Patent count				Trademark count				IPR bundle (dummy)			
			Elast	z-value	95% CI		Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.18	3.48	0.08	0.28	0.12	2.17	0.01	0.22	0.17	1.53	-0.05	0.39
	Yes	Incumbent	0.52	7.59	0.39	0.66	0.20	4.80	0.12	0.28	0.36	2.61	0.09	0.63
	Yes	Startup	0.58	8.36	0.44	0.71	0.23	5.65	0.15	0.31	0.46	3.79	0.22	0.70
RC	No	Incumbent	0.15	2.61	0.04	0.26	0.12	2.01	0.00	0.23	0.09	0.78	-0.14	0.33
	Yes	Incumbent	0.52	7.14	0.38	0.67	0.20	4.41	0.11	0.29	0.40	2.89	0.13	0.66
	Yes	Startup	0.56	8.90	0.44	0.69	0.28	6.90	0.20	0.36	0.50	4.35	0.27	0.72
SKF	No	Incumbent	0.21	3.93	0.11	0.31	0.11	2.20	0.01	0.20	0.12	1.21	-0.07	0.32
	Yes	Incumbent	0.59	9.43	0.47	0.71	0.17	4.71	0.10	0.24	0.45	4.42	0.25	0.65
	Yes	Startup	0.60	9.30	0.47	0.73	0.24	6.40	0.16	0.31	0.53	4.46	0.30	0.76
No. of obs.			34,517				34,493				34,448			
Pseudo R^2			0.52				0.21				0.40			
Total patent counts[1]			860				441				532			
Total tradem. counts[2]			408				2,724				431			
Total design counts[3]			140				171				152			

Dependent variable is the number of applications of the given IPR type in a time interval $[T, T+5)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same 5-year interval. Robust standard errors (SE). Startup firms are ≤ 3 years old at the time of treatment assignment (other firms are incumbents). Notes: [1] Number of patents in final estimation sample conditional on non-zero dependent variable [2] Number of trademarks in final estimation conditional on non-zero dependent variable. [3] Number of designs in final estimation sample conditional on non-zero dependent variable.

Table 7: Expected number of additional IPR per NOK million in increased support (*Addit*), measured over $n-$year intervals ($n = 3$ and $n = 5$)

Instr.	Firm char. (f)		IPR type																	
	R&D-start.	Age-group	Patent count						Trademark count						Total IPR count					
			$n=3$			$n=5$			$n=3$			$n=5$			$n=3$			$n=5$		
			Addit	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI	
INR	No	Incum.	.02	-.02	.05	.02	.00	.04	.02	-.01	.06	.02	-.01	.04	.03	-.01	.07	.03	.00	.05
	Yes	Incum.	.01	-.01	.03	.01	-.01	.03	.02	.00	.05	.02	.00	.04	.02	.00	.05	.02	.00	.05
	Yes	Startup	.04	.01	.06	.03	.01	.06	.04	.02	.07	.02	.00	.05	.07	.04	.10	.05	.02	.07
	Mean (over f)		.02	-.01	.05	.02	.00	.04	.03	.00	.06	.02	.00	.04	.04	.01	.07	.03	.00	.06
RC	No	Incum.	.01	-.01	.02	.00	.00	.01	.01	-.01	.02	.00	.00	.01	.01	.00	.03	.01	.00	.02
	Yes	Incum.	.01	-.01	.03	.01	.00	.03	.01	.00	.03	.01	.00	.02	.01	-.01	.03	.02	.00	.04
	Yes	Startup	.01	.00	.02	.03	.02	.04	.02	.01	.03	.01	.01	.02	.03	.02	.05	.03	.02	.04
	Mean (over f)		.01	.00	.02	.01	.01	.02	.01	.00	.03	.01	.00	.02	.02	.00	.03	.02	.01	.03
SKF	No	Incum.	.03	-.01	.06	.04	.01	.07	.02	-.01	.05	.02	-.01	.04	.04	.00	.07	.04	.01	.07
	Yes	Incum.	.01	.00	.03	.02	.00	.03	.03	.01	.05	.02	.00	.04	.03	.01	.05	.03	.01	.05
	Yes	Startup	.03	.01	.05	.02	.00	.03	.03	.01	.05	.02	.01	.04	.05	.03	.08	.04	.02	.06
	Mean (over f)		.02	.00	.05	.03	.01	.05	.03	.01	.05	.02	.00	.04	.04	.02	.07	.04	.01	.06
All	No	Incum.	.02	-.01	.04	.02	.00	.04	.02	-.01	.04	.01	-.01	.03	.03	.00	.05	.03	.00	.05
	Yes	Incum.	.01	-.01	.03	.01	.00	.03	.02	.00	.04	.02	.00	.03	.02	.00	.04	.02	.00	.05
	Yes	Startup	.03	.01	.05	.03	.01	.04	.03	.01	.05	.02	.01	.03	.05	.03	.07	.04	.02	.06
	Mean (over f)		.02	.00	.04	.02	.00	.04	.02	.00	.05	.02	.00	.03	.03	.01	.06	.03	.01	.05

Estimated expected number of additional IPR per NOK million in increased support over $n-$year intervals $[T, T+n)$, using Equation (4). See Footnote 19 for details and formulae for calculation of confidence intervals. Startup firms are ≤ 3 years old at the time of treatment assignment, while other firms are incumbents. R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. “All” refers to unweighted average across main policy instruments.

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Appendix A: Double selection

The double election procedure proceed in three step, following Belloni et al. (2016).

Step 1: Single selection. Run a Lasso-Poisson regression of $P_{i,[T,T+n)}$ on y_{iT} and x_{iT} using all $(i,T) \in \cup_{dj}\mathbb{Y}(d,j)$ (the aggregate risk set):

$$(\widetilde{\alpha}^0,\widetilde{\beta}^0) = \arg\min_{\alpha,\beta}\sum_{d,j}\sum_{(i,T)\in\mathbb{Y}(d,j)} -l_{dj}(x_{iT};\alpha_{dj},\beta) + \frac{\lambda_1}{N}||\beta||_1$$

where $\alpha = \{\alpha\}_{dj}$ and

$$l_{dj}(x;\alpha_{dj},\beta) = P_{i,[T,T+s)}\left(s_{dj}(\overline{S}_i,\alpha_{dj})y_{iT}(d,j)+\beta x\right) - \exp(s_{dj}(\overline{S}_i,\alpha_{dj})y_{iT}(d,j)+\beta x)$$

is the Poisson log-likelihood, λ_1 is the regularization parameter and $||\cdot||_1$ refers to the L_1-norm (see Belloni et al. 2016 for details).

Step 2: Double selection. For every $d \in \{1,...,n\}$ and $j \in \mathscr{P}$ run logistic Lasso-regression of $y_{iT}(d,j)$ on x_{iT} conditional on (i,T) being included in the risk set $\mathbb{Y}(d,j)$:

$$\widetilde{\theta}^0_{dj} = \arg\min_{\theta}\sum_{(i,T)\in\mathbb{Y}(d,j)} -\Lambda_{dj}(x_{iT};\theta) + \frac{\lambda_2}{N}||\theta||_1$$

where λ_2 is a regularization parameter and

$$\Lambda_{dj}(x;\theta) = y_{iT}(d,j)\theta x - \ln(1+\exp(\theta x))$$

is the log-likelihood of the logit model.

Step 3: Post (double) selection estimation. “Double selection" refers to the components of x_{iT} selected by Lasso either in Step 1 (the components with corresponding non-zero $\widetilde{\beta}^0$) or in step 2 (the components with corresponding non-zero $\widetilde{\theta}^0_{dj}$ for some (d,j)). Let supp(δ) denote the index set of non-zero coefficients of the vector δ. Then the post selection estimates $\widetilde{a}$ and $\widetilde{\beta}$ are:

$$(\widetilde{a},\widetilde{\beta}) = \arg\min_{a,\beta}\sum_{d,j}\sum_{(i,T)\in\mathbb{Y}(d,j)} l_{dj}(x_{iT};\alpha_{dj},\beta) : \text{supp}(\beta) \subseteq \text{ supp}(\widetilde{\beta}^0)\bigcup_{dj}\text{ supp}(\widetilde{\theta}^0_{dj})$$

and

$$\widetilde{\theta}_{dj} = \arg\min_{\theta}\sum_{(i,T)\in\mathbb{Y}(d,j)} \Lambda_{dj}(x_{iT};\theta)\ \text{supp}(\theta) \subseteq \text{ supp}(\widetilde{\beta}^0)\cup\text{supp}(\widetilde{\theta}^0_{dj})$$

Appendix B: Proof of Proposition 1

By direct calculations:

$$\frac{\partial Q_{dj}(\alpha_{dj};\widetilde{\beta},\widetilde{\theta})}{\partial\widetilde{\beta}} = -\sum_{(i,T)\in\mathbb{Y}(d,j)} w_{iT}(d,j)v_{dj}(x_{iT};\widetilde{\theta}_{dj})x_{iT} \tag{13}$$

with

$$w_{iT}(d,j) = \exp(s_{dj}(\overline{S}_i, \widehat{\alpha}_{dj})y_{iT}(d,j) + \widetilde{\beta}x_{iT}). \tag{14}$$

Replacing $(\alpha_{dj}, \widetilde{\theta}, \widetilde{\beta})$ with $(\alpha^0_{dj}, \theta^0, \beta^0)$ gives the first equality since $E(v_{dj}(x_{iT}; \theta^0_{dj})|D_i = d, J_i = j, T_i = T, x_{iT}) = 0:$

Next,

$$\frac{\partial Q_{dj}(\alpha_{dj}; \widetilde{\beta}, \widetilde{\theta})}{\partial \widetilde{\theta}} = -\sum_{(i,T)\in\mathbb{Y}(d,j)} \omega_{iT}(d,j)u_{dj}(x_{iT}; \alpha_{dj}, \widetilde{\beta})x_{iT} \tag{15}$$

where

$$\omega_{iT}(d,j) = p_{dj}(\widetilde{\theta}_{dj}x_{iT})(1 - p_{dj}(\widetilde{\theta}_{dj}x_{iT})). \tag{16}$$

Again, replacing $(\alpha_{dj}, \widetilde{\theta}, \widetilde{\beta})$ with $(\alpha^0_{dj}, \theta^0, \beta^0)$ gives the second equality since $E(u_{dj}(x_{iT}; \alpha^0_{dj}, \beta^0)|D_i = d, J_i = j, T_i = T, x_{iT}) = 0$.

Finally,

$$\frac{\partial R_{dj}(\alpha_{dj}; \widetilde{\beta})}{\partial \widetilde{\beta}} = -\sum_{(i,T)\in\mathbb{Y}(d,j)} w_{iT}(d,j)y_{iT}(d,j)\left(\ln(\overline{S}_i) - \overline{s}(d,j)\right)x_{iT}$$

The last equality in (12) follows directly from $E(\ln(\overline{S}_i) - \overline{s}(d,j)|D_i = d, J_i = j, T_i = T, x_{iT}) = 0$.

Appendix C: Estimates of control variable coefficients and supplementary results for manufacturing and services

Table 8: Dependent variable: Patent counts. Estimates of selected control variable coefficients after double selection. Temporal interval width: $n = 3$

Control variables	Coeff.	SE	z	P>z
Share college educated empl.	0.79	0.27	2.87	0.00
Sum patents	0.03	0.01	5.16	0.00
3.Patents	1.84	0.56	3.29	0.00
i.Employees # j.Patents				
1 # 2	8.42	1.23	6.86	0.00
1 # 3	7.00	1.30	5.40	0.00
2 # 2	1.76	0.66	2.64	0.01
3 # 2	1.85	0.61	3.06	0.00
4 # 2	1.97	0.89	2.22	0.03
i.Employees # j.Age				
1 # 1	0.43	0.21	1.98	0.05
4 # 1	−8.92	0.52	−17.11	0.00
2.R&D # 1.Employees	−7.35	1.19	−6.19	0.00
1.R&D # 1.Patents	−3.23	0.51	−6.28	0.00
2.R&D # 1.Age	−2.84	0.56	−5.07	0.00

Note: Coefficients with $|z| > 1.96$ are shown, except for time- and industry dummies which are included but not shown. The notation $i.X$ refers to the level (i) of an ordinal variable X. The notation # refers to interaction between two variables, e.g. $i.X\#j.Y$ (indicated by i # j in the table). "i.Patents" refer to zero ($i = 1$), one ($i = 2$) or more than one ($i = 3$) previous patents applications. "i.Employees" refer to < 5 ($i = 1$), $5 - 49$ ($i = 2$), $50 - 250$ ($i = 3$) or > 250 ($i = 4$) employees. "i.Age" refers to < 4 ($i = 1$), $4 - 9$ ($i = 2$), $10 - 20$ ($i = 3$) or > 20 ($i = 4$) years. "i.R&D" refers to R&D-inactive ($i = 1$) of R&D-active ($i = 2$).

Table 9: Dependent variable: Trademark counts. Estimates of selected control variable coefficients after double selection. Temporal interval width: $n = 3$

Control variables	Coeff.	SE	z	P>z
Share college educated empl.	0.42	0.13	3.20	0.00
Share with higher second. educ.	0.38	0.13	2.96	0.00
Employment growth rate	0.34	0.08	4.16	0.00
3.Tradem	1.84	0.16	11.60	0.00
i.Employees # j.Age				
3 # 3	0.62	0.15	4.15	0.00
4 # 3	0.90	0.37	2.41	0.02
i.Age # j.Tradem				
1 # 3	−0.82	0.26	−3.12	0.00
2 # 2	1.04	0.19	5.49	0.00

Note: Coefficients with $|z| > 1.96$ are shown, except for time- and industry dummies which are included but not shown. The notation $i.X$ refers to the level (i) of an ordinal variable X. The notation # refers to interaction between two variables, e.g. $i.X\#j.Y$ (indicated by i # j in the table). “i.Tradem” refer to zero ($i = 1$), one ($i = 2$) or more than one ($i = 3$) previous trademark filings. “i.Employees” refer to < 5 ($i = 1$), $5-49$ ($i = 2$), $50-250$ ($i = 3$) or > 250 ($i = 4$) employees. “i.Age” refers to < 4 ($i = 1$), $4-9$ ($i = 2$), $10-20$ ($i = 3$) or > 20 ($i = 4$) years.

Table 10: Manufacturing: Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 3-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j). GMM estimates after Lasso-based double selection of control variables

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)							
	R&D-starter	Age-group	Patent count				Trademark count			
			Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.16	1.60	-0.04	0.36	-0.09	-1.03	-0.26	0.08
	Yes	Incumbent	0.30	2.68	0.08	0.52	0.08	0.94	-0.08	0.23
	Yes	Startup	0.26	2.31	0.04	0.49	0.19	2.64	0.05	0.33
RC	No	Incumbent	0.19	2.21	0.02	0.36	-2.35	-11.81	-2.74	-1.96
	Yes	Incumbent	-1.83	-11.24	-2.15	-1.51	-0.06	-0.35	-0.38	0.26
	Yes	Startup	-0.92	-5.79	-1.24	-0.61	0.16	1.89	-0.01	0.33
SKF	No	Incumbent	0.22	2.46	0.04	0.39	-0.05	-0.69	-0.21	0.10
	Yes	Incumbent	0.38	3.52	0.17	0.59	0.06	0.88	-0.08	0.21
	Yes	Startup	0.29	2.72	0.08	0.51	0.19	2.85	0.06	0.32
No. of obs.			7,809				7,803			
Pseudo R^2			0.47				0.26			
Total patent counts[1]			286				144			
Total tradem. counts[2]			107				449			

Dependent variable is the number of applications of the corresponding IPR type in a time interval $[T, T+3)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same 3-year interval.Robust standard errors (SE). Startup firms are $\leq$ 3 years old at the time of treatment assignment (other firms are incumbents). R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. Notes: [1] Number of patents in final estimation sample conditional on non-zero dependent variable [2] Number of trademarks in final estimation conditional on non-zero dependent variable. [3] Number of designs in final estimation sample conditional on non-zero dependent variable.

Table 11: Manufacturing: Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 5-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j). GMM estimates after Lasso-based double selection of control variables

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)							
	R&D-starter	Age-group	Patent count				Trademark count			
			Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.20	2.43	0.04	0.35	0.07	0.80	-0.10	0.23
	Yes	Incumbent	0.38	3.38	0.16	0.59	0.18	2.16	0.02	0.33
	Yes	Startup	0.35	3.54	0.16	0.54	0.19	2.35	0.03	0.35
RC	No	Incumbent	0.27	3.16	0.10	0.43	0.04	0.45	-0.14	0.23
	Yes	Incumbent	-6.44	-33.40	-6.82	-6.06	0.23	2.19	0.02	0.43
	Yes	Startup	0.31	2.90	0.10	0.53	0.24	3.36	0.10	0.38
SKF	No	Incumbent	0.20	2.54	0.05	0.36	0.06	0.68	-0.11	0.22
	Yes	Incumbent	0.48	4.18	0.26	0.71	0.14	1.92	0.00	0.29
	Yes	Startup	0.36	3.46	0.15	0.56	0.21	2.76	0.06	0.35
No. of obs.			6,035				6,026			
Pseudo R^2			0.49				0.27			
Total patent counts[1]			347				272			
Total tradem. counts[2]			232				588			

Dependent variable is the number of applications of the corresponding IPR type in a time interval $[T, T+5)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same n-year interval. Robust standard errors (SE). Startup firms are ≤ 3 years old at the time of treatment assignment (other firms are incumbents). R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. Notes: [1] Number of patents in final estimation sample conditional on non-zero dependent variable [2] Number of trademarks in final estimation conditional on non-zero dependent variable. [3] Number of designs in final estimation sample conditional on non-zero dependent variable.

Table 12: Services: Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 3-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j). GMM estimates after Lasso-based double selection of control variables

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)							
	R&D-starter	Age-group	Patent count				Trademark count			
			Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.22	2.23	0.03	0.41	0.24	2.99	0.08	0.40
	Yes	Incumbent	0.55	4.55	0.31	0.79	0.30	6.33	0.21	0.40
	Yes	Startup	0.61	8.12	0.46	0.75	0.37	7.66	0.28	0.47
RC	No	Incumbent	-0.12	-0.92	-0.38	0.14	0.23	2.25	0.03	0.43
	Yes	Incumbent	0.56	5.54	0.36	0.75	0.27	4.30	0.15	0.39
	Yes	Startup	0.52	6.98	0.38	0.67	0.35	6.74	0.25	0.45
SKF	No	Incumbent	0.12	1.21	-0.07	0.31	0.18	3.00	0.06	0.30
	Yes	Incumbent	0.56	6.28	0.39	0.74	0.29	6.80	0.21	0.38
	Yes	Startup	0.57	7.44	0.42	0.72	0.35	7.53	0.26	0.44
No. of obs.			35,819				35,810			
Pseudo R^2			0.45				0.21			
Total patent counts[1]			392				65			
Total tradem. counts[2]			106				1,923			

Dependent variable is the number of applications of the corresponding IPR type in a time interval $[T, T+3)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same 3-year interval. Robust standard errors (SE). Startup firms are $\leq$ 3 years old at the time of treatment assignment (other firms are incumbents). R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. Notes: [1] Number of patents in final estimation sample conditional on non-zero dependent variable [2] Number of trademarks in final estimation conditional on non-zero dependent variable. [3] Number of designs in final estimation sample conditional on non-zero dependent variable.

Table 13: Services: Estimated elasticities (b_j^f) of IPR outcomes with respect to support dose over 5-year intervals, by firms' pre-treatment characteristics (f) and main policy instrument (j). GMM estimates after Lasso-based double selection of control variables

Main instr. (j)	Firm characteristics (f)		Dependent variable (IPR type)							
	R&D-starter	Age-group	Patent count				Trademark count			
			Elast	z-value	95% CI		Elast	z-value	95% CI	
INR	No	Incumbent	0.29	3.42	0.13	0.46	0.13	1.22	-0.08	0.34
	Yes	Incumbent	0.64	6.74	0.45	0.83	0.24	4.91	0.15	0.34
	Yes	Startup	0.72	8.55	0.55	0.88	0.27	5.51	0.18	0.37
RC	No	Incumbent	0.05	0.49	-0.15	0.25	0.21	3.29	0.09	0.34
	Yes	Incumbent	0.65	7.71	0.48	0.81	0.24	4.53	0.13	0.34
	Yes	Startup	0.67	8.46	0.52	0.83	0.33	7.10	0.24	0.42
SKF	No	Incumbent	0.27	3.19	0.10	0.44	0.17	2.46	0.04	0.31
	Yes	Incumbent	0.67	8.23	0.51	0.83	0.22	4.96	0.13	0.30
	Yes	Startup	0.74	8.74	0.58	0.91	0.27	5.97	0.18	0.36
No. of obs.			27,044				27,027			
Pseudo R^2			0.47				0.19			
Total patent counts[1]			455				133			
Total tradem. counts[2]			164				2,083			

Dependent variable is the number of applications of the corresponding IPR type in a time interval $[T, T+5)$, except for IPR bundle which is a dummy variable (0 or 1) of having both patents and at least one other type of IPR in the same 5-year interval. Robust standard errors (SE). Startup firms are ≤ 3 years old at the time of treatment assignment (other firms are incumbents). R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. Notes: [1] Number of patents in final estimation sample conditional on non-zero dependent variable [2] Number of trademarks in final estimation conditional on non-zero dependent variable. [3] Number of designs in final estimation sample conditional on non-zero dependent variable.

Table 14: Manufacturing: Expected number of additional IPR per NOK million in increased support (*Addit*), measured over $n-$year intervals ($n = 3$ and $n = 5$)

Instr.	Firm char. (f)		IPR type																	
	R&D-start.	Age-gr.	Patent count						Trademark count						Total IPR count					
			$n=3$			$n=5$			$n=3$			$n=5$			$n=3$			$n=5$		
			Addit	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI	
INR	No	Incu.	.02	.00	.03	.02	.00	.04	-.01	-.03	.01	.01	-.01	.03	.00	-.04	.05	.03	-.01	.07
	Yes	Incu.	.01	.00	.01	.01	.00	.01	.01	-.01	.02	.02	.00	.03	.01	-.01	.03	.02	.00	.04
	Yes	Start.	.01	.00	.02	.02	.01	.03	.02	.01	.04	.02	.00	.04	.03	.01	.06	.04	.01	.07
	Mean (over f)		.01	.00	.02	.02	.01	.03	.01	-.01	.02	.01	.00	.03	.02	-.01	.04	.03	.00	.06
RC	No	Incu.	.02	.00	.04	.01	.00	.02	.00	.00	.00	.00	.00	.01	.02	.00	.04	.01	.00	.03
	Yes	Incu.	.00	.00	.00	.00	.00	.00	.00	-.01	.01	.01	.00	.02	.00	-.01	.01	.01	.00	.02
	Yes	Start.	-.01	-.01	.00	.02	.01	.03	.01	.00	.02	.01	.01	.02	.00	-.01	.01	.03	.01	.05
	Mean (over f)		.00	.00	.01	.01	.00	.02	.00	.00	.01	.01	.00	.02	.01	-.01	.02	.02	.00	.03
SKF	No	Incu.	.06	.01	.11	.05	.01	.10	-.01	-.03	.02	.01	-.02	.04	.05	-.02	.12	.06	-.01	.14
	Yes	Incu.	.02	.01	.03	.02	.01	.03	.00	-.01	.01	.02	.00	.03	.02	.00	.04	.04	.02	.06
	Yes	Start.	.02	.01	.04	.02	.00	.03	.02	.01	.03	.02	.01	.04	.04	.01	.07	.04	.01	.07
	Mean (over f)		.03	.01	.06	.03	.01	.05	.00	-.01	.02	.02	.00	.03	.04	.00	.08	.05	.01	.09
All	No	Incu.	.03	.00	.06	.03	.01	.05	-.01	-.02	.01	.01	-.01	.02	.02	-.02	.07	.04	-.01	.08
	Yes	Incu.	.01	.00	.01	.01	.01	.02	.00	-.01	.01	.01	.00	.03	.01	.00	.02	.02	.01	.04
	Yes	Start.	.01	.00	.02	.02	.01	.03	.02	.00	.03	.02	.00	.03	.02	.00	.05	.04	.01	.06
	Mean (over f)		.02	.00	.03	.02	.01	.03	.00	-.01	.02	.01	.00	.03	.02	-.01	.05	.03	.00	.06

Estimated expected number of additional IPR per NOK million in increased support over $n-$year intervals $[T, T+n)$, using Equation (4). See Footnote 19 for details and formulae for calculation of confidence intervals. Startup firms are ≤ 3 years old at the time of treatment assignment, while other firms are incumbents. R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. "All" refers to unweighted average across main policy instruments.

Table 15: Services: Expected number of additional IPR per NOK million in increased support (*Addit*) , measured over $n-$year intervals ($n = 3$ and $n = 5$)

Instr.	Firm char. (f)		IPR type																	
	R&D-start.	Age-gr.	Patent count						Trademark count						Total IPR count					
			$n = 3$			$n = 5$			$n = 3$			$n = 5$			$n = 3$			$n = 5$		
			Addit	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI		*Addit*	95% CI	
INR	No	Incum.	.03	.00	.06	.04	.02	.06	.04	.01	.07	.03	-.05	.10	.08	.02	.14	.07	-.03	.17
	Yes	Incum.	.01	.01	.01	.01	.01	.02	.03	.02	.04	.03	-.01	.06	.04	.02	.05	.04	.00	.07
	Yes	Start.	.05	.03	.06	.05	.04	.06	.05	.03	.06	.03	.00	.06	.09	.07	.11	.08	.04	.12
	Mean (over f)		.03	.01	.04	.03	.02	.05	.04	.02	.06	.03	-.02	.07	.07	.04	.10	.06	.00	.12
RC	No	Incum.	.00	-.01	.00	.00	.00	.00	.02	.00	.04	.01	.00	.02	.02	-.01	.04	.01	.00	.02
	Yes	Incum.	.02	.01	.02	.02	.01	.02	.01	.01	.02	.01	.00	.03	.03	.02	.04	.03	.01	.05
	Yes	Start.	.02	.01	.02	.03	.02	.04	.02	.02	.03	.02	.01	.02	.04	.03	.05	.05	.03	.06
	Mean (over f)		.01	.01	.02	.02	.01	.02	.02	.01	.03	.01	.00	.02	.03	.01	.04	.03	.02	.04
SKF	No	Incum.	.01	-.01	.04	.04	.01	.06	.03	.01	.04	.03	-.01	.06	.04	.00	.08	.06	.01	.12
	Yes	Incum.	.01	.01	.02	.02	.01	.02	.03	.02	.04	.03	.00	.05	.04	.03	.06	.04	.02	.07
	Yes	Start.	.03	.02	.04	.02	.01	.03	.04	.03	.05	.03	.01	.05	.07	.05	.09	.05	.02	.08
	Mean (over f)		.02	.01	.03	.02	.01	.04	.03	.02	.04	.03	.00	.05	.05	.03	.07	.05	.01	.09
All	No	Incum.	.01	.00	.03	.03	.01	.04	.03	.01	.05	.02	-.02	.06	.04	.00	.08	.05	-.01	.10
	Yes	Incum.	.01	.01	.02	.02	.01	.02	.02	.02	.03	.02	.00	.04	.04	.02	.05	.04	.01	.06
	Yes	Start.	.03	.02	.04	.03	.02	.04	.04	.03	.04	.03	.01	.04	.07	.05	.08	.06	.03	.08
	Mean (over f)		.02	.01	.03	.02	.01	.03	.03	.02	.04	.02	.00	.05	.05	.03	.07	.05	.01	.08

Estimated expected number of additional IPR per NOK million in increased support over $n-$year intervals $[T, T+n)$, using Equation (4). See Footnote 19 for details and formulae for calculation of confidence intervals. Startup firms are ≤ 3 years old at the time of treatment assignment, while other firms are incumbents. R&D-starters are firms without any R&D activity in the preceding five years. Treated startups are classified as R&D-starters. "All" refers to unweighted average across main policy instruments.