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12th Norwegian German Seminar on Public Economics

Munich, 5 – 6 November 2021

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For Whom the Patent Pays: Firm Behaviour Before, During and After a Patent Application♣

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October 2021

Abstract
In most OECD countries, the gross domestic spending on research and development (R&D) is substantial, on average 2.5 percent of gross domestic product. A large share of the R&D expenditures, including research in the business enterprise sector, is funded by the governments. This paper investigates empirically the dynamics between firms' employment, output, success in obtaining public research funding, labour productivity, return on assets (ROA), and capital intensity in the periods before, during, and after filing a patent application. The analysis is based on a panel of accounting data for all Norwegian firms merged with patent application data from the Norwegian Industrial Property Office (NIPO). The final panel covers a period of 18 years (2001-2018). Since the sample includes the whole population of Norwegian firms, it allows to form both a large control- and treatment-group (firms that file at least one patent application in the period). year a patent application A patent has significant positive effects on employment, output and public research funding both in periods before, during and after it is filed. The effects are largest at the extensive margins, i.e. largest for firms without any prior patent applications. Additional patents have small or insignificant effects. We also find that there is a negative correlation between R&D support and age. The overall finding is therefore that patents are important in the early in the life-cycle of firms.

Keywords: Patenting, Firm Performance, Firm-level Data.
JEL classification: C33, D22, O34

♣ Acknowledgements: We would like to thank Stefano Breschi for fruitful discussions. We acknowledge financial support from the Research Council of Norway through grant 256240 (OSIRIS).

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1. Introduction

In 2018, the average gross domestic spending on R&D was 2.5 percent of gross domestic product in OECD countries.[1] For Norway, R&D expenditure was close to NOK 73 billion, which corresponds to 2.1 percent of gross domestic product. In terms of FTEs, 45 percent of R&D work was carried out in the business enterprise sector while 55 percent in the university, college, and institute sectors. Additionally, around 10 percent of research in the business enterprise sector is funded by the public through the Research Council of Norway, Innovation Norway and the R&D tax deduction scheme SkatteFUNN.[2] In other words, there is a significant amount of public funding to foster R&D.

Economists have established innovation as a vital factor to economic growth and social welfare, and governments actively seek to spur innovative activities. While public funding is one instrument, the patenting system can be reckoned as another public policy to promote innovation. The economic rationale behind patents is anchored in the *knowledge spillover effect*, which, together with *limited appropriability* and financial constraints, demonstrate that there are positive external effects not considered by market actors when deciding how much to invest in R&D. The existence of market failure, in the sense that it is difficult to establish ownership rights to new production methods or technologies, enables competitors to take advantage of investment in R&D without bearing the costs. Nelson (1959) and Arrow (1962) proved how – in the absence of intellectual property regulation – firms are unable to get a return on their innovation investment due to imitation by rivals. The *knowledge spillover* effect indicates that positive externalities rise from innovation because other market players can build upon it. Meanwhile, the *appropriability problem* occurs because entrepreneurs need to show at least parts of the innovation publicly, to communicate its novelty and commercialize it (Arrow 1962;

[1] https://www.oecd.org/sti/msti-highlights-march-2021.pdf

[2] See for instance Nilsen et al. (2020) for a more comprehensive description of the various public R&D funding schemes.

Nelson 1959; Teece 1986; Tirole 1988). Economic literature describes two main mechanisms through which patent rights promote innovation. The first - "reward theory" - argues inducing ex ante incentives by giving exclusivity, and thus monopoly rents from the innovation (Nordhaus, 1969). Whereas the "contract theory" incorporates patents' social contribution of information sharing, signifying a contract by which the innovator will receive a reward in return for providing information about her innovation (Eisenberg, 1989; Arrow, 1962).

Over the years, theoretical contributions have challenged the underlying assumptions of the patent system. Many researchers have found that entrepreneurs often have intrinsic motivation and are driven by factors other than money (Giuri et al. 2006; Maurer and Scotchmer, 2006), some also use innovations as signals to the job market, showing money may not always be the main incentive (Lakhani and Wolf, 2005; Lerner and Tirole, 2002). On top of that, the traditional view of knowledge as a public good has been challenged, as it is shown to be costly and difficult to imitate. Boldrin and Levine (2002) show that first-mover advantage can be sufficient to let inventors recoup their R&D investment. More recently, extensive literature has emerged on the strategic effect of patent rights (E.g.: Comino and Manenti, 2020; Graham et al., 2010; Arundel, 2001; Shapiro, 2001; Cohen et al., 2000). Firms use patent portfolios as protection against rival firms taking legal action for patent infringement (Ziedonis, 2004). They may want to use them aggressively against competitors and suppliers in negotiations (Walsh et al., 2016; Torrisi et al., 2016), as well as to block competitors from innovating in certain areas. Patent thickets also limit firms' freedom of action in R&D, increasing the cost of innovation (Shapiro, 2001). Leyva-de la Hiz et al. (2021) argues that environmental innovating firms protect their investments from opportunism by generating a large amount of patented marginal innovations in domains central to their industry, thus limiting environmental progress. Furthermore, Sweet and Eterovic (2019) argue that a patent has no significant effect on national productivity growth, finding that technological application is more significant than intellectual property rights in spurring productivity growth. Torrisi et al. (2016) find that around 40% of all patents remain unused, and 26% remain unused for strategic reasons.

The effectiveness of patent rights, compared to other innovation-promoting systems, remains unclear. As it appears, economists do not fully capture the institutional aspects of patent systems. This study aims to shed light on processes related to innovations and patenting at the firm level. We use a dataset with the population of Norwegian firms followed from 1995 to 2018. For these firms we have accounting data, firm data, such as the employment stock, and all patent applications for the same period. These data are scrutinised by auditing firms and the Tax Administration before being made available for aggregate public statistics and research. In addition, we have merged the accounting data and the patent applications with survey data on firms' R&D-expenditures. The R&D survey data combine two sources: the annual R&D census and questionnaire data from firms that have applied for tax credits. The questionnaire data contain information about R&D expenditures each year during the three previous years. Combining the two R&D surveys enables us to track the recent R&D history of about 85 percent of the firms that obtained any form of public R&D support during the observation period. With these sets of information merged, we are investigating empirically the dynamics between firms' output, employment, labour productivity, and R&D activity in the periods before, during, and after filing a patent application. A long time period, together with using the whole populations of Norwegian firms, allow us to form both a large control- and treatment-group. Using these rich, high-quality data, the main findings show that a firm which do activities that end up with a patent application has an increase in activity, measured as employment, output and the likelihood of getting public R&D support. The increase starts already two years before the actual (and first) patent application is filed. For the two first outcomes, employment and output the increase is substantial and last at least three or more years after the patent application is filed. The likelihood of getting R&D support vanishes after three years.

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

The paper continues as follows. In Section 2 data are described, while Section 3 explains the empirical specification. In Section 4, we discuss the empirical results. Section 5 gives concluding remarks and suggests some policy implications.

2. Data

2.1 Data sources

We start out with administrative data including Norwegian firms' balance sheet information, accounting data, and industry codes spanning the years from 1995 to 2018. The main source of information in this database is based on the compulsory firms' annual financial accounts and employment information. These data have universal coverage. The fact that they are collected for public registration and scrutinized by auditing firms and the Tax Administration before release implies that they are of high quality. These initial data are merged with data on innovation policies and the related R&D questionnaire data, which are collected from 2002, when the tax credit scheme *Skattefunn* was introduced in Norway, and onwards.

The balance sheet information is merged with patent data collected from the Norwegian Industrial Property Office (NIPO). This dataset includes all patent applications filed in Norway in the period from 1995 to 2018. In total, there are about 5,000 firms (organizational numbers) filing at least one patent application in our sample. The Norwegian patent data contain unique firm identification numbers that allow for a reliable match of patent data to the other data sets. Data on innovation policies are obtained from SSB's Policy instrument database.[3] These data sources are used to obtain information related to R&D support for all the firms in the Business Registry from 2002 and onwards.[4]

Our primary source of information about firms' R&D expenditure is the Business R&D census.[5] 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.

We focus on the following set of annual outcome variables; (1) $\ln(L)$ - log number of employees, (2) $\ln(Y)$ - log output – measured as value added in NOK millions (NOK 100 ≈ EUR 11), (3) public research support – *pubsupp* - an indicator function which is one if the company receives public research support in the given year, (4) $\ln(Y/L)$ - log labour productivity, (5) *RoA* – return on assets - profit divided by the book value of total assets, and (6) capital intensity (total assets per employee).[6] We have used a winsorization method for $\ln(Y/L)$ and *RoA* by putting values below the 1^{th} and above 99^{th} percentile equal to the value at their respective percentile. The reason is that these variables are vulnerable to measurement errors, especially when the denominator is small.

[3] (Norwegian;) Virkemiddeldatabasen.
[4] If more than one firm participates in a project, the data from the PROVIS-database are only available for the main contractor firm.
[5] The census has been annual since 2001 and was bi-annual from 1995 to 1999.
[6] See Table A1 for more detailed variable definitions.

2.2 Descriptive statistics

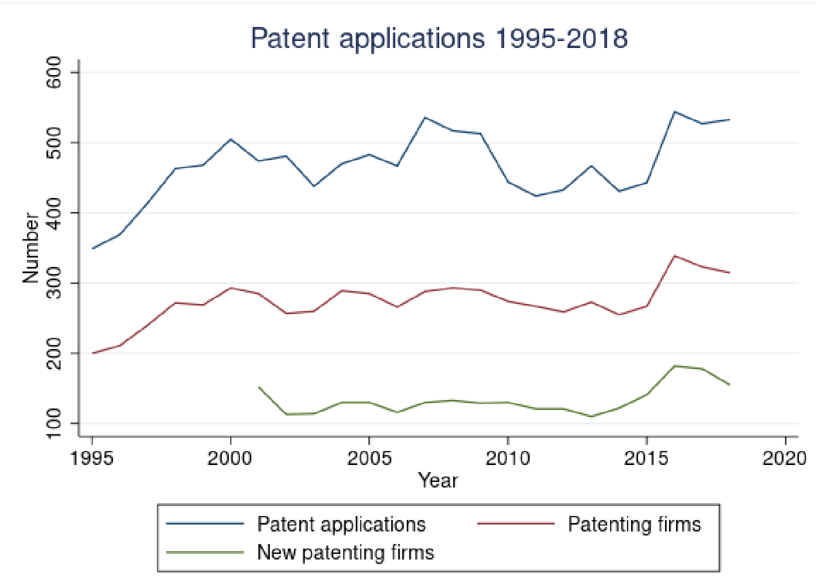

Figure 1. Total filed patent applications in Norway (1995-2018)

From Figure 1 we see that there is an increase in patent applications and number of patent applying firms during 1995-2007, except for a sharp drop related to the burst of the IT bobble around 2001-2003. Then there was a new sharp decline in total patent applications during the Great Recession, with number of patent applications not returning to the pre-crisis level until 2016. In 2016, the oil price shock hit the Norwegian economy, with an adverse effect on patenting in 2017-2018. We also observe in Figure 1 that there are considerably more patent applications than there are patent applying firms. In fact, more than 40% of the total applications were filed by firms with two or more applications in a given year. The largest number of applications in one firm-year (one firm observed in one year) is 35. Still, the major part of applications (60%) comes from firms with one application in a given year. New patenting firms, i.e. firms with no registered previous patent application, make up about 40% of patenting firms in a given year. The graph for "new patenting firms" is shown for 2001-2018, assuming that firms without any patent applications in 1995-2000, have no applications prior to 1995 neither.

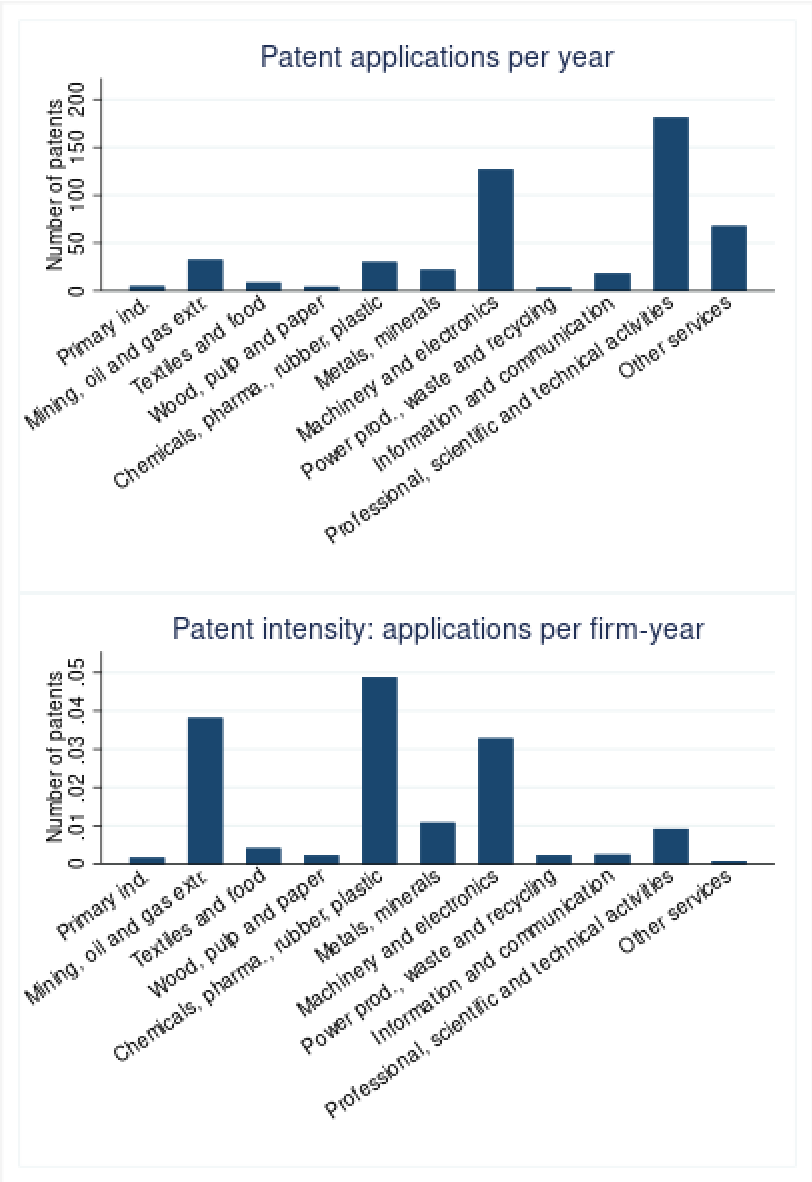

Figure 2. Number of patent applications per year or firm-year, by industry

Figure 2 depicts the average number of patent applications per year by industry (upper panel) defined at different levels of industry aggregation, and the number of patents per firm-year (lower panel). Most applications are filed in the five manufacturing industries depicted (especially in Machinery and electronics), Professional, scientific and technical activities, Other services and Mining, oil and gas extraction. The lower panel reveals large differences between the industries with regard to the *intensity* of patenting, i.e. number of applications relative to number of firms (firm-years) in each industry. The three top industries with respect to patent intensity are Manufacturing of chemical, pharmaceutical, rubber and plastic products; Manufacturing of machinery and electronics; and Mining, oil and gas extraction. Then comes Manufacturing of metals and minerals and Professional, scientific and technical activities. Other industries have an almost negligible number of patent applications per firm-year, but a large share of total applications.

Table 1. Descriptive statics for variables of main interest, 2001-2018. Mean and median values per firm-year, by industry and whether a firm has any patent applications

	Manfacturing				Services[1)]			
	Patenting firm[2)]		All firms		Patenting firm		All firms	
Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median
No. of patent appl.	0.278	0	0.018	0	0.239	0	0.003	0
No. of employees	101.5	16.0	19.9	4.0	32.2	2.0	7.8	2.0
Labor productivity[3)]	570	545	453	402	562	560	456	393
Return on assets (RoA)	0.04	0.06	0.05	0.05	0.00	0.02	0.06	0.05
Assets per employee	1693	1135	1040	605	1909	1306	984	540
Dummy of R&D-support	0.47	0	0.10	0	0.34	0	0.02	0
Firm-age	17.3	13.0	13.3	10.0	11.6	8.0	10.2	7.0
Dummy of start-up firm[4)]	0.14	0.00	0.22	0.00	0.24	0.00	0.30	0.00
No. of firms	1,044		22,505		2,142		245,240	

Note: [1)] Mainland service industries, i.e. excluding oil services and sea transport. [2)]At least one patent application during 2001-2018. [3)] Value added (output) in NOK 1000 per employee [4)]Firm-age <=3 years in the given firm-year.

Table 1 shows descriptive statistics for the variables of main interest for Manufacturing and Services. Manufacturing is obtained by aggregating the five manufacturing industries depicted in Figure 2: Textiles and food, Wood, pulp and paper, Chemicals, pharma, rubber, plastic, Metals and minerals and Machinery and electronics. Services is obtained by aggregating all mainland non-financial service industries: Power prod, waste and recycling, Information and communication, Professional, scientific and technical activities, and Other services. We see that the employment distribution is skewed, and the median number of employees is far below the average. Generally, firms in manufacturing are larger than in services (see No. of employees, and output). There are 1,044 patenting firms in Manufacturing and 2,142 in Services in the period 2001-2018. We note that the mean and median of patenting firms are much larger than the mean and median of all firms. Patenting firms are also more productive, measured by value added (output) per employee, and more capital intensive measured by assets per employee. However, patenting firms are not more profitable, measured by mean or median RoA. Finally, patenting firms obtained public R&D support in 47% and 34% of the firm-year in manufacturing and services during 2001-2018, respectively. The corresponding shares among all firms are 10% and 2%.

3. Empirical specification

We want to study the performance of firms before, during and after the occurrence of a patent application, which we consider as a proxy of a (patent) *invention*. To do so, we first define a dummy variable, S_{it}, which indicates at least one application in year *t* by firm *i.* Second, we define the variable τ_i as the first year of patenting:

$$\tau_i = \min\left\{t : S_{it} = 1\right\}$$

Third, we define the indicator function Z_{jit} which is one if $t = \tau + j$:

$$Z_{jit} = \begin{cases} 1 & \text{if } t = \tau + j \\ 0 & \text{otherwise} \end{cases},$$

Thus, by definition $Z_{0i\tau_i} = 1$. Finally, we define a vector of dummy variables:

$$Z_{it} = (Z_{-2,it}, Z_{-1,it}, Z_{0,it}, Z_{1,it}, Z_{2,it}, \sum_{j>2} Z_{jit})'$$

Z_{0it} equals one if the firm had its first patent application in year *t,* Z_{-1it} equals one if it had its first application in *t+1* and Z_{-2it} equals one if the first application occurs in *t+2*. Similarly, $Z_{1it}=1$ if the first application occurs in *t-1* and $Z_{2it}=1$ if this happened in t-2. Finally, the last component $\sum_{j>2} Z_{jit}$ equals one if the first patent application occurred 3 or more years ago.

Note that at most one component of Z_{it} can be non-zero for given *t*. If the firm has additional patent applications in τ_i+1 or τ_i+2, then these applications will be part of the same *patent invention*. Thus, $Z_{0i,\tau+1}=Z_{0i,\tau+2}=0$ even if additional patent applications are filed in $\tau+1$ or $\tau+2$. However, if the firm obtains a new patent in $\tau+3$ or later, we will consider this as a second patent invention.

In order to estimate different effects for first time patenting (extensive margin) and repeated patenting (intensive margin), our approach accommodate repeated patenting by conditioning on the number of previous patent applications. Formally, we define

$$\tau_i^{(n)}=\min\{t>\tau_i^{(n-1)}+2 : S_{it}=1\} \text{ for } n\geq 2$$

and $\tau_i^{(1)}=\tau_i$. Thus $\tau_i^{(1)}=\tau_i$ – the first year of patenting – while for $n\geq 2$, $\tau_i^{(n)}=t$ if the firm has a patent in *t* and at least three years have passed since the *previous* invention. For integers *n* we define $Z_{it}^{(n)}$ analogously to Z_{jit}, i.e. with τ_i replaced by $\tau_i^{(n)}$.

Our regression equation for studying the effect of the *n*'th patent invention is:

$$Y_{it}=\beta^{(n)}Z_{it}^{(n)}+\gamma^{(n)}U_{it}+v_i^{(n)}+\varepsilon_{it}^{(n)} \text{ for } \tau_i^{(n-1)}+2<t<\tau_i^{(n+1)}-2 \text{ and } n=1,2,3...$$

where Y is a dependent variable: log-employment, log-output (value added), labour productivity, returns to assets (RoA), capital intensity (assets per employee), or an indicator of whether the firm obtained public R&D support in *t* (we define $\tau_i^{(0)}$ as 2 years before the firm's birth year, implying $\tau_i^{(1)} = \tau_i$). The vector *U* consists of exogenous control variables: time dummies and firm-age dummies. The firm-age dummies are included to capture differences in firm-dynamics between start-up firms, young firm and old firms, which is potentially a confounding factor. For example, first time patenting is expected to be negatively correlated with age. Finally, $v_i^{(n)}$ is a fixed effect and $\varepsilon_{it}^{(n)}$ an idiosyncratic error term with a distribution that potentially depends on *n*.

For the group of firms that has not filed any patent application by *t+2*, the outcome variable Y_{it} fluctuates randomly around $\gamma^{(1)}U_{it} + v_i^{(1)}$, where the common movement is given by $\gamma^{(1)}U_{it}$. By contrast, firms that file the first patent application at *t*, i.e., firms with $Z_{0it} = 1$, may differ systematically from other firms, both before, during and after the patent application, as determined by $\beta^{(1)} = (\beta_{-2}^{(1)},....,\beta_2^{(1)},\beta_{>2}^{(1)})$. If the first patent filing occurs in year *t*, this is accompanied by a shift in $Y_{i,t-2}$ equal to $\beta_{-2}^{(1)}$, a shift in $Y_{i,t-1}$ equal to $\beta_{-1}^{(1)}$ and a shift in Y_{it} equal to $\beta_0^{(1)}$. In the year just after an application, there is a shift equal to $\beta_1^{(1)}$, and then $\beta_2^{(1)}$ in the year after. The permanent long-term effect is assumed to be $\beta_{>2}^{(1)}$. All these shifts are relative to not having *any* patent applications as of *t+2*.

The panel series used to estimate $\beta^{(n)} = (\beta_{-2}^{(n)},...,\beta_2^{(n)},\beta_{>2}^{(n)})$ consist of the firm-years *after* $\tau_i^{(n-1)} + 2$ and *before* $\tau_i^{(n+1)} - 2$ for all firms with at least *n-1* patent inventions (i.e. firms for which $\tau_i^{(n-1)}$ has a non-missing value). The rationale is that the effect of the *n-1'*th patent invention *after* $\tau_i^{(n-1)} + 2$ equals $\beta_{>2}^{(n-1)}\sum_{j>2} Z_{jit}^{(n-1)}$, which is captured by the fixed effect $v_i^{(n)}$ related to the potential *n'th* invention. Note that heterogeneity in the long-term *effects* of patenting is captured by $v_i^{(n)}$. Thus our model allows endogenous selection based on the "success" of previous patenting. The panel series must end before $\tau_i^{(n+1)}-2$ to be consistent with the effect $\beta_{-2}^{(n+1)}Z_{-2,it}^{(n+1)}$ of the *next* patent invention at $\tau_i^{(n+1)}$ (if non-missing).

We apply fixed effect regression models and regress Y_{it} on $Z_{it}^{(n)}$ and U_{it} to estimate $\beta^{(n)}$ and $\gamma^{(n)}$. The fixed effects models use an OLS estimator on time-demeaned variables capturing the time variation within firms. The model is estimated separately for manufacturing and services.

4. Empirical results

Below we present graphs of the estimated coefficients, the β-s of the various periods relative to the time of a patent application and for the various variables of interest. The graphs in Figure 3, illustrate how firms in the manufacturing and service industry evolve from two year before the first application at τ compared to not having had any patent applications as of t+2. The table with the underlying regression results is found in the appendix (Table A2).

Extensive margins

We start out with a sample for which there are initially (either in 2001 or the firm's founding year) are no *previous* patents. Thus, we focus here on what we refer to as the extensive results, i.e. going from zero to one patent innovation. Then we measure the evolvement of the variables relative to the year (τ) when the patent application is filed.

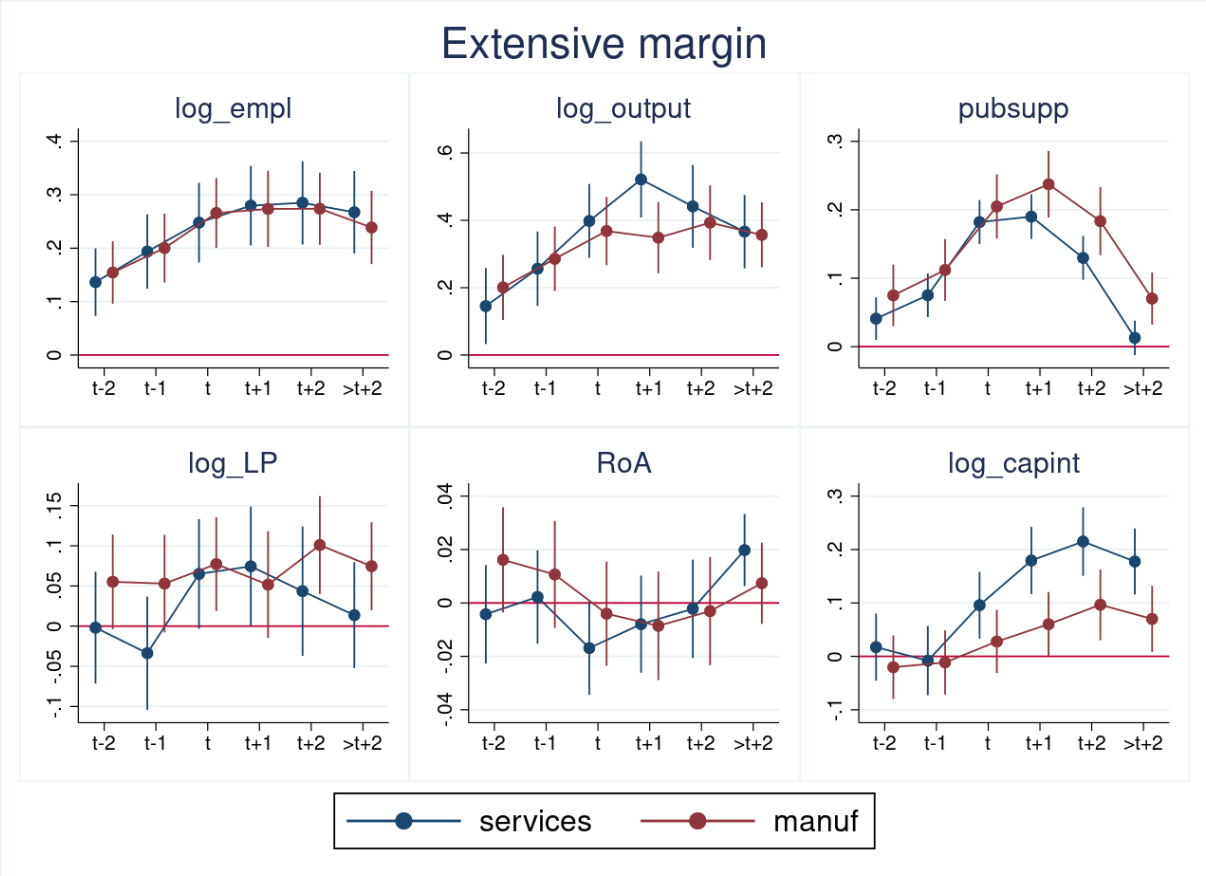

Figure 3. Extensive margin. Plot of coefficient estimates with confidence intervals

At first sight, there are several significant coefficients displayed in Figure 3 (t in the figure should be read as τ), implying that a patent invention affects both firms' input and output variables. The magnitudes of the coefficients seem to be reasonable – indicating persistent increased level of the variables in the range from 25 to 35 per cent three or more years after the invention. We also observe that the development for manufacturing and service firms are very similar. This is somewhat surprising, as the two industries are structurally different. For example, we saw from Table 1 that manufacturing firms are larger and older than the firms in the service industry. It should, however, be noted the results are related to patenting firms, which have quite similar characteristics across industries according to Table 2. This raises the issue of sample selection effects. The potential problem of selection is (hopefully) mitigated by the use of fixed effects, which controls for time-invariant firm characteristics that could be correlated with the explanatory variables. The results show that employment and output in both industries begin to increase significantly already two year before the patent application. For both variables, it seems like the level is approximately 15-20 percent higher two years before to the patent filing compared to the what would have been the level without the patent. This is not a simple artefact of self-selection, because of the firm-specific fixed effects.

The increase in the probability of getting public R&D support is of the same order of magnitude as the effect on employment and output growth. However, this probability drops markedly in year t+2 compared to $t+1$ and t, and then drops towards the $t-2$ level in the years after. This does not mean that these firms do not persistently get more public R&D funding than the average firm: it means that there is a positive relation between closeness to the time of patenting and the probability of getting public support for the firms that actually patent.

Turning to the ratio variables, labour productivity, RoA and capital intensity, the effect of a patent application is more uncertain, and mostly statistically insignificant. We observe that there is a significant spike in labour productivity two years after the first application, and that the effect persists in the years after. This is a plausible result as it should take time for the patented invention to be incorporated in the firm after the application is filed. The same can be interpreted for the significant modest increase in profitability for service firms more than two years after the application. Moreover, the examination of granted patents (which are available for a much shorter time period), indicates that about 2/3 of the applications are granted, and thus lead to a valuable intellectual property right (IPR). If we look at the capital intensity figure and hold this together with the employment figure (which is the denominator in the capital intensity figure), we see that, on average, a patent application increases capital intensity (including intangible assets). The effect on capital intensity is at its largest two years after the first patent application.

A positive effect on output and input variables is supported by an extensive literature. Of the few studies that use patents or patent applications to study firm dynamics, the effect usually becomes manifest after the application is filed (Munari, 2013). In the case of both services and manufacturing firms, we find that the output effect is largest in the years after the patent application is filed. Yet, for both industries the effect on output is already present in the year before the application, which could imply that the innovation is developed and used before the application is approved and sometimes even before applying. This is, however, not an unreasonable implication, because the patent application requires information disclosure, and the firm might want to develop it fully and use other protection mechanisms before filing the patent applications. The result showing increased employment before the patent application, on the other hand, is less surprising. Although there is no real evidence from economic literature regarding when an innovation have effects on employment, the result we observe indicates that the firm chooses to increase its employee stock the year before applying for a patent. This makes sense from the firm's point of view, since it expects increased economic activity in the future as a result from the patent and the underlying invention. Another, more debateable explanation can be related to firms' signalling effect in the job market, luring talents by presenting the firm as attractive and capable of innovating (Lerner and Tirole, 2002).

Age differences

Table 2: Age-difference estimates from the extensive margin analyses

	Manufacturing						Services					
	log_empl	log_outpu	pub. supp	L. product	ROA	Cap.intens.	log_empl	log_outpu	pub. supp	L. product	ROA	Cap.intens.
4-10 yrs old	0.167	0.292	-0.008	0.128	0.012	0.062	0.121	0.221	-0.002	0.121	0.008	0.073
	(0.009)	(0.013)	-0.003	(0.008)	(0.002)	(0.009)	(0.002)	(0.003)	(0.000)	(0.002)	(0.001)	(0.003)
11-20 yrs old	0.259	0.382	-0.012	0.104	0.015	0.058	0.170	0.220	-0.003	0.085	0.009	0.065
	(0.015)	(0.021)	-0.004	(0.011)	(0.003)	(0.013)	(0.004)	(0.005)	(0.000)	(0.004)	(0.001)	(0.004)
20+ yrs old	0.263	0.334	-0.010	0.073	0.010	0.043	0.136	0.098	-0.003	0.014	0.000	0.039
	(0.020)	(0.030)	-0.007	-0.016	(0.004)	(0.019)	(0.006)	(0.008)	(0.001)	(0.006)	(0.001)	(0.006)

In Table 2 we report the estimated age-difference dummies from the extensive margin analyses. The age-dummies are control variables representing life-cycle dynamics. The respective age groups are: start-up firms (the reference category), defined as firms equal to or less than 3 years; 4-10 year old firms; 11-20 year old firms; and firms above 20 years. From the regression tables we observe that all the coefficient's signs are the same for manufacturing and services, and that most of them are significant. The only significantly negative coefficient is related to public R&D-support, implying that older firms are less likely to receive R&D support than start-up firms. Admittedly, the magnitude of these negative coefficients are rather small. Note that there are no noteworthy differences between the three oldest age categories with respect to the probability to receive support. The estimated relation between age, on the on side, and employment and output, on the other, is not surprising. Larger firms have, on average, more employees and higher output. For labor productivity, start-up firms have significantly lower productivity than incumbent firms, with the highest productivity found in the age categories 4-20 years. This finding is in line with Brasch and Raknerud (2021). Likewise, profitability also depends on firm age, with firms between 4 and 20 years being the most profitable. Start-up firms are, not surprisingly, the least profitable firms on average. Finally, age seems to be negatively correlation with capital intensity.

Intensive margin

For the intensive margin we study the effect of repeated patenting, rather than the case for the extensive margin where we observe the effect of the *first* patent application. The graphs show weighted average estimated effects over $n = 2,3$ (*t* in the figure should be interpreted as $\tau_i^{(n)}$ for $n = 2,3$). Looking at the development of log-employment in Figure 4, we observe a similar pattern as for the extensive margin, though with smaller magnitude and fewer significant variables. In particular, none of the long-term effects (i.e. lasting beyond the second year after the patent invention) are significant, except for capital intensity. This effect indicates that the long-term effect of repeated patenting is an increase in assets related to the patenting (i.e. IPR). However, we should be careful not to over-interpret the finding, as there is no such pattern for manufacturing, and for services, the effect is barely significantly at the 95 % level. The (robust) confidence intervals are also wide, reflecting the small number of firms with repeated patent applications (recall that two patent applications must be at least 3 years apart by definition).

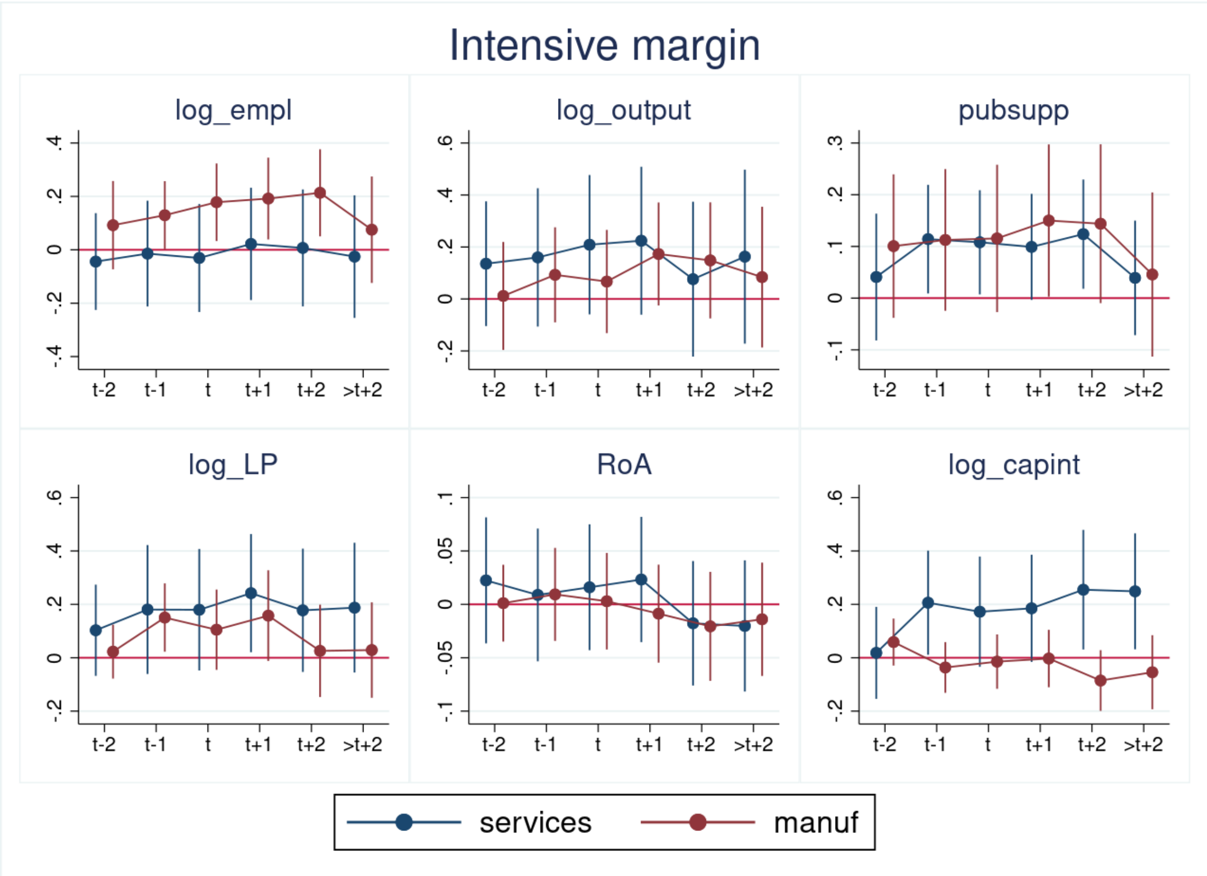

Figure 4: Plot of intensive margin coefficients

5. Concluding remarks

Given that patenting, together with significant public R&D support, is a very important instrument to spur innovative activities, and that innovation is established as a vital factor to economic growth and social welfare, it is of great importance to increase our knowledge on how firms respond and take advantage of the patent right. In this paper we do that micro-econometrically by utilizing a dataset with the population of Norwegian firms followed from 1995 to 2018. For these firms we have accounting data, employment data, and patent applications for the same period. We have merged these data with survey data on firms' R&D-expenditures to investigating empirically the dynamics between firms' output, employment, labour productivity, and research and development (R&D) activity in the periods before, during, and after filing a patent application. The long observation period, together with using the whole populations of Norwegian firms, allow us to form both a large control- and treatment-group.

The findings in this paper show that a firm which do activities that end up with a patent application has an increase in activity, measured as employment, output and the likelihood of getting public R&D support. The effect starts already two years before the actual (and first) patent application is filed. For the two first outcomes, employment and output the increase is substantial and last at least three or more years after the patent application is filed. The likelihood of getting R&D support vanishes after three years. The effect of a patents on labour productivity and profitability seems to be relatively unaffected, and if any effect it appears in the years after the application. Out of the analysed outcome variables, capital intensity seems to be slower in responding relative to employment and output, as we mainly see an effect after two years. Somewhat surprisingly, the differences between the manufacturing industry and the service industry seem to be rather modest. When focusing on age-differences between the firms, older firms have, on average, more employees and higher output. For labor productivity, start-up firms have significantly lower productivity than incumbent firms, with the highest productivity found in the age categories 4-20 years. Likewise, profitability also depends on firm age, with firms between 4 and 20 years being the most profitable. Without surprise, start-up firms are the least profitable firms on average.

Concentrating on the intensive margin, the overall findings is that these margins, i.e. the effects of an additional patent filing given that the firms already has a recent one, are positive but rather modest and hardly statistically significant. Findings with significant effects on the extensive margins but small for intensive margin, lead to potentially strong policy implications. R&D support should be directed to promote innovations at the extensive margin, i.e. to firms with a high potential of becoming innovative rather than to firms that already have a record of being innovative. Moreover, as targeted subsidies generate more innovations, society benefits from distributing much of the subsidies to priority areas. Such a finding is in line with other studies also based on Norwegian data (see for instance Nilsen et al. (2020), and Brasch and Raknerud (2021)). Whether such a pattern is present also in other countries, is still an open question. Nevertheless, based on the present findings, the existence of a properly working patenting system seems to be economically important.

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Appendix

Table A1 Variable definitions.
To be completed

Table A2: Regression coefficients – extensive margins
To be completed

Table A3: Regression coefficients – intensive margins
To be completed

Table A4: Regression coefficients – extensive margins – firm size differences
To be completed