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Dynamics of First-Time Patenting Firms

Abstract

This paper investigates firm dynamics in the period before, during, and after an event consisting of a first published patent application. The analysis is based on patent data from the Norwegian Industrial Property Office merged with data from several business registers covering a period of almost 20 years. We apply an event study design and use matching to control for confounding factors. The first patent application by a young firm is associated with significant growth in employment, output, assets and public research funding. Moreover, our results indicate that economic activity starts to increase at least three years ahead of the first patent application. However, we find no evidence of additional firm growth after patent approval for successful applicants. Our findings indicate that the existence of a properly functioning patenting system supports innovation activities, especially early in the life cycle of firms.

JEL-Codes: C330, D220, O340.

Keywords: patenting, firm performance, panel data, event study design.

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1. Introduction

It is common knowledge that innovation is a vital factor for economic growth and social welfare (see e.g., Aghion et al., 2009; Kogan et al., 2017; Rebelo, 1991). The existence of market failure, for example the difficulty of establishing ownership rights to new production methods or technologies, has led governments to intervene in the market for intangible property rights – or “intangible capital” more generally – using a wide set of policy instruments. While public R&D may be the most widely analysed among such instruments, the patent system is also an important tool for promoting innovation (Fontana et al., 2013). One way in which the patent system may play an important role in intangible capital formation is by facilitating access to capital from private investors and public agencies, thereby promoting R&D and innovation in the business enterprise sector (see Link and Scott, 2018).

This paper aims to contribute to knowledge about how firms benefit from patenting early in their life cycle, with potential implications for a variety of stakeholders, such as policy makers, regulators, entrepreneurs, managers, and potential investors. Specifically, we investigate firm performance in the period before, during, and after the event of filing the first patent application. Our sample consists of all Norwegian limited liability firms that might potentially have filed their *first* application in the course of the years 2001-2018. As a consequence, the sample is dominated by small, young firms. This feature of our data is important, as a well-functioning patent system might provide especially strong incentives for entrepreneurs, thus contributing to economic growth and innovativeness in a Schumpeterian sense (see Sengupta, 2014).

Patents have been a cornerstone of innovation metrics for several decades (see Mansfield, 1986; Griliches, 1990; Archibugi and Pianta, 1992; Lerner, 2005). While patents have acknowledged strengths as an indicator of innovation output, the propensity to patent is known to be skewed towards large firms in a few R&D-intensive industries, especially in manufacturing (see Dernis and Guellec, 2001). Inventions can also be protected by means of intellectual property rights (IPR) other than patents, e.g. industrial design and trademarks (see Flikkema et al., 2019), by a combination of different IPRs ("IPR bundling"), or even by secrecy. Nevertheless, there seems to be a lack of worthy substitutes. For example, trademark data are typically available only for a few (recent) years, whereas innovation measures based on surveys, such as the Community Innovation Survey (CIS), are prone to measurement errors as they depend on the respondents' self-reporting (Brouwer and Kleinknecht, 1997).[1] It is also well documented that patenting is strongly correlated with R&D and innovative activities in general (see e.g. the discussion in Bronzini and Piselli, 2016, and Svensson, 2022). Several studies use patent counts as a measure of innovation in evaluations of R&D policies; Bronzini and Piselli (2016) find that an R&D subsidy program in Italy has a significant effect on the increase in the number of patent applications, with a more pronounced effect on small firms than on large ones. Dechezleprêtre et al. (2016) find that tax deductions for R&D expenses in the UK increased the propensity to patent. Cappelen et al. (2012) find that the introduction of R&D tax credits in Norway contributed to an increase in (self-reported) new products and processes, but not to more patent applications.

Our patent data were collected from the Norwegian Industrial Property Office (NIPO), the patent authority in Norway. We use a dataset covering all Norwegian limited liability firms from 1995-2018. The Norwegian patent data come with an administrative firm identifier, which means that we can merge patent data with a wealth of information from other public registers. In most countries, there is no unique identifier allowing researchers to link intellectual property information directly to other firm-level data. For example, PATSTAT

[1] Comparing the data from the Norwegian CIS with registered patent applications from the Norwegian Patent Office reveals large discrepancies with regard to both the timing and the number of patent registrations, raising serious concerns about the quality of self-reported measures of innovation in general.

and the US patent office provide identification only in the form of names.[2] Although the patent offices have harmonized the use of names within their organizations, harmonization with other data sources is challenging (Helmers et al., 2011; Tarasconi and Kang, 2016). We merge patent data with registers containing a wealth of information in order to investigate the dynamics between firm performance in the periods before, during, and after the first filing of a *published* patent application (henceforth referred to as "first-time patenting firms"). Our empirical methodology is that of an event study design with a matched control group, where some firms in the panel become first-time patenting firms, but at random times (see Freyaldenhoven et al., 2019). It is important to have a sufficiently large treatment group and a large reference population from which to draw the control group in order to mitigate problems related to self-selection and endogeneity. We will argue that matching combined with fixed effects regression facilitates causal interpretations.

Our main findings are that patenting firms experience a significant increase in economic activity well ahead of their first patent application. The patent event has a huge effect on variables related to economies-of-scale such as employment, output and total assets: over a period of five years *before* to five years *after* its first application, the growth rate of a patenting firm is 3-5 percentage points (p.p.) higher *per year* than that of a matched control group. There also appears to be a persistent effect on the outcome variables beyond that interval, as there is no sign of a mean reversion six years after the patent event. Regarding access to funding, we find that the probability of securing public R&D support increases during a three-year period before the application, and eventually stabilizes at a significantly higher level after the application date than before.

In our study, the event of interest is that of a patent application published within 18 months, when publication (disclosure) of the patent applied for is mandatory. Our study is

[2] See Graham et al. (2018) for a study matching U.S. patents to administrative databases on firms and workers, using the names indicated on patent documents, including assignee and inventor names, and the firm names contained in firm-level databases, in order to merge data sets.

related to, but distinctly different from, recent contributions to the literature on the effects of the patenting system. For example, while we attempt to measure the value of patenting relative to not having any patent applications, Farre-Mensa et al. (2020) estimate the *incremental* value of the IPR above the value of the underlying innovation. Because the value of an innovation without the IPR would depend on the counterfactual method of protection (e.g. secrecy), the distinction between the value of the patented innovation and the value of the legal protection (the IPR *per se*) is challenging: the counterfactual outcome here involves both an intensive margin (some firms may invest less in R&D without the legal protection) and an extensive margin (some firms may not undertake innovation projects at all). In any case, the value of the IPR cannot be identified without strong identifying assumptions.[3] Another recent study by Hegde and Luo (2018) investigates the effect on (the timing of) licensing contracts of a change in U.S. patent law in 1999 that made publication (disclosure) of patent applications mandatory 18 months after the date of the filing of the application. A related, older study by Bloom and van Reenen (2002) examines the effects on total factor productivity of citation-weighted patents using a neo-classical (Cobb-Douglas) production function framework. Our event-design study differs from all the aforementioned studies by examining a much broader set of economic indicators related to economies of scale and profits, by doing so over a longer period (before and after) the event, and by using an event study design with matching to control for confounding factors.

The rest of the paper is organized as follows: a description of the data is provided in Section 2, Section 3 provides the empirical specification, while in Section 4 we discuss the empirical results. Section 5 provides concluding remarks and suggests some policy implications emerging from our findings.

[3] Farre-Mensa et al. (2020) use a measure of variation in individual evaluator leniency as an instrumental variable.

2. Data

2.1 Data sources

Our patent data were collected from the Norwegian Industrial Property Office (NIPO). NIPO is responsible for process applications and approval of patent rights, trademarks and designs in Norway.[4] The national schemes for industrial rights in Norway are characterized by a high degree of harmonisation with regulations and practices in Europe, and cooperation with international intellectual property rights organizations, for instance the Nordic Patent Institute (NPI), the European Patent Office (EPO), and the World Intellectual Property Organization (WPO). The NIPO data include all patent applications filed in Norway in the period from 1995 to 2021. Conditional on approval by NIPO based, among other things, on an initial review of the application's claim of novelty and payment of a substantial fee, an application is published 18 months after the application date. According to NIPO, only about 50 percent of filed applications are published and less than 30 percent are approved.

Our focus will be on firms that filed their first public patent application in 2001-2018, using the wider period 1995-2020 to identify first-time patenting firms and approved patent applications.[5] Patent applications that were not published are not included in our data set. Moreover, we focus on manufacturing and mainland service industries, i.e. excluding petroleum-related services and shipping. This yields about 2,500 *first-time* patenting firms (organizational numbers) in 2001-2018.

We merged the patent data with several administrative registers spanning the years from 1995 to 2018 with data on accounting variables, number of employees, founding year,

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[4] As in other countries, the IPR of a business in Norway could be "rented out", licensed, or sold. A patent provides a limited time for invention (up to 20 years, with increasing annual fees) and must be published after 18 months. Furthermore, a patent has a low price initially, with increasing annual fees to encourage the patent owner to give up the monopoly rights. See also Qiu et al. (2018) describing US patents involving Norwegian inventors and assignees.

[5] According to NIPO, the average waiting time from application to grant is five years and the median waiting time is 3 years. Duration is endogenous and depends on the timeline of the firm's actions (e.g. payments of fees) at the different stages of the application process.

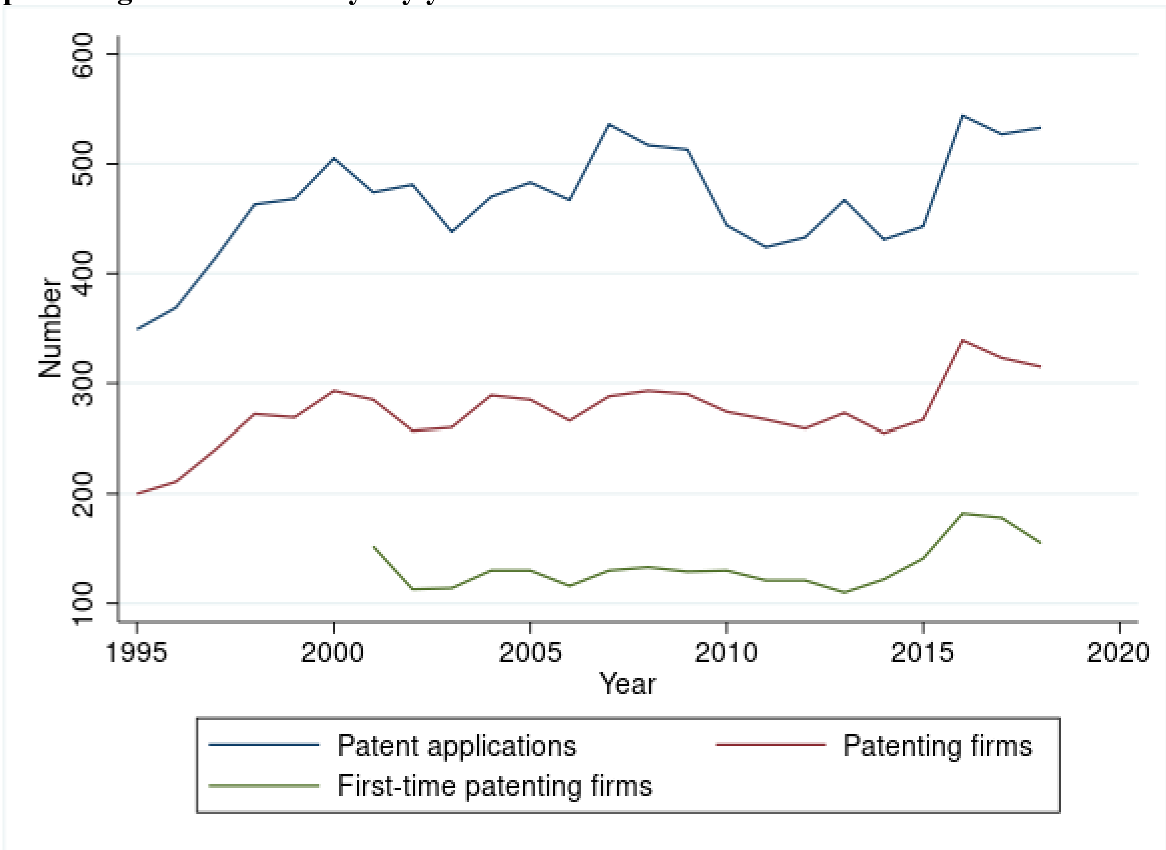
industry code, etc. These data are based on firms' annual financial accounts and employment registers and have universal coverage. The fact that the data are compulsory and scrutinized by auditors and the Norwegian Tax Administration before release imply that they are of high quality. Furthermore, these data are merged with information on public R&D support from Norway's universal (rights-based) tax credit scheme (*Skattefunn).*[6]

2.2 Descriptive statistics

From Figure 1 we see that there was an increase in (published) patent applications and the number of firms applying for patents firms in 1995-2007, except for a sharp drop related to the bursting of the IT bubble around 2001-2003. Then there was a new sharp decline in total patent applications during the Great Recession, with the number of patent applications not exceeding the pre-crisis level until 2016. We also observe in Figure 1 that there were considerably more patent applications than firms with patent applications: more than 40% of all applications were filed by firms with two or more applications in a given year. First-time patenting firms, i.e., firms with no previous registered patent application, make up about 40% of all patenting firms in a given year.

[6] These data were obtained from Statistics Norway's Policy Instrument Database (in Norwegian: "Virkemiddeldatabasen").

Figure 1. Number of total published patent applications, patenting firms and first-time patenting firms in Norway. By year

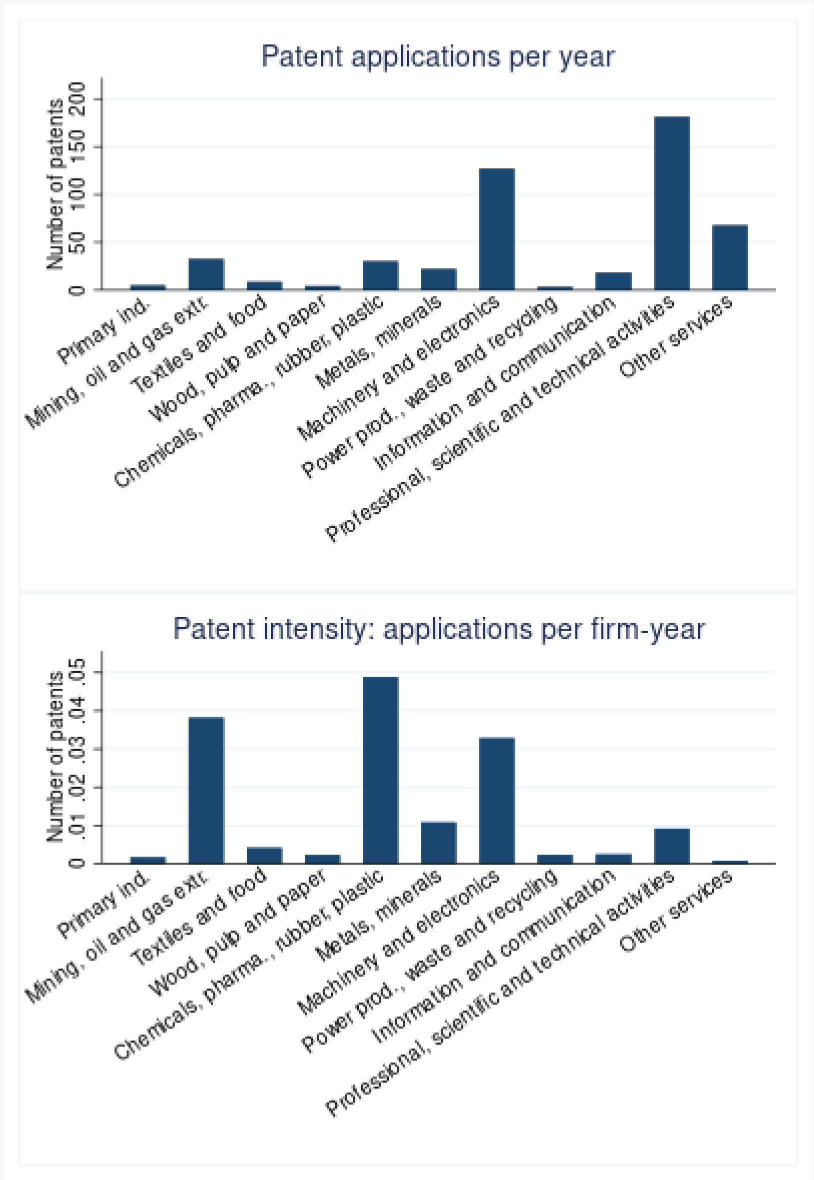


Note: We identify first-time patenting firms in 2001-2018 as firms with no patent applications in 1995-2000. Firms in financial services and commercial real estate are excluded.

Figure 2 depicts the average number of patent applications per year by industry (excluding financial services and commercial real estate) in the upper panel, and the number of patents per firm-year in the lower panel. Most applications were filed in "Professional, scientific and technical activities", "Machinery and electronics", "Other services", "Mining, oil and gas extraction" and "Chemicals, pharma, rubber, plastic". The lower panel reveals large differences between the industries with respect to the *intensity* of patenting, i.e., number of applications relative to number of firm-years[7] in each industry.

[7] One firm observed in one year.

Figure 2. Number of patent applications per year and patent intensity, by industry



The three top industries with respect to patent intensity were "Chemicals, pharmaceutical, rubber and plastic products", "Machinery and electronics", and "Mining, oil and gas extraction". Next come "Metals and minerals" and "Professional, scientific and technical activities". "Other services" have an almost negligible number of patent applications per firm-year, but a large share of total applications.

In the following, we will focus on two broadly defined industry groups: Manufacturing and Services, where Manufacturing is the aggregate of the five manufacturing industries, i.e., "Textiles and food", "Wood, pulp and paper", "Chemicals, pharma, rubber, plastic", "Metals and minerals" and "Machinery and electronics", and Services is the aggregate of the three mainland non-financial service industries: "Information and communication", "Professional, scientific and technical activities", and "Other services". Thus, we exclude "Primary industries", "Mining, oil- and gas extraction" and "Power production, waste and recycling" (in addition to financial services and commercial real estate) from our analyses. Table 1 shows descriptive statistics for the variables of main interest, with 1,193 firms applying for patents in Manufacturing and 2,412 in Services (henceforth referred to as *applicant firms*). Of these, 744 and 1,843 were first-time patenting firms in 2001-2018. We see that the distribution of number of employees is skewed, with the median far below the average. Generally, firms in Manufacturing are larger than in Services (see no. of employees). The mean and median numbers of employees in applicant firms are much larger than the means and medians of all firms, as has also been documented by many others (Athreye et al., 2021 is a recent example). First-time patenting firms are on average younger and smaller than overall applicant firms, reflecting the fact that the latter group also includes firms with patent applications predating 2001. Applicant firms are more productive, measured by value added (output) per employee, and more capital intensive, measured by assets per employee, than non-patenting firms. However, they are not more profitable in terms of mean or median return on assets.[8] Furthermore, applicant firms obtained public R&D support in 45% and 33% of the firm-years in Manufacturing and Services, respectively, in 2001-2018. The corresponding shares among all firms are only 10% and 2%. The median firm ages of applicant firms are 14 and 9 years in Manufacturing and Services, respectively, whereas the median firm ages of first-time patenting firms and *all* firms are equal: 11 years in Manufacturing and 7 years in

[8] We have used winsorization for the rate variables (labor productivity and return on assets) by setting values below the 1th and above the 99th percentile equal to the value at their respective percentiles. The reason is that these variables are susceptible to measurement errors, especially when the denominator is small.

Table 1. Descriptive statistics for applicant vs. all firms

	Manufacturing						Services[1)]					
	Applicant firms[2)]		First-time patenting firms[3)]		All firms		Applicant firms		First-time patenting firms		All firms	
Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
No of patent applications [4)]	0.28	0.00	0.24	0.00	0.02	0.00	0.24	0.00	0.25	0.00	0.00	0.00
No. of employees	97.68	16.0	66.70	12.00	19.32	3.00	32.20	2.00	24.52	2.00	7.79	1.00
Log no. of employees	3.22	3.18	2.96	2.83	1.93	1.79	2.01	1.79	1.92	1.79	1.46	1.39
Assets per employee[5)]	1,866	1,302	1,797	1,208	1,160	692	2,051	1,464	2,081	1,488	1,063	590
Labor productivity[6)]	612.78	610.00	589.99	591.00	498.85	460.50	591.40	621.00	576.16	603.00	494.64	443.00
Return on assets (RoA)[7)]	0.04	0.05	0.02	0.05	0.05	0.04	0.00	0.01	-0.01	0.00	0.06	0.04
Dummy of R&D support	0.45	0.00	0.46	0.00	0.10	0.00	0.33	0.00	0.36	0.00	0.15	0.00
Firm age	18.28	14	15.41	11	14.11	11	12.05	9	10.28	7	10.41	7
Share start-up firms[8)]	0.12	0	0.17	0	0.21	0	0.22	0	0.28	0	0.30	0
Share small firms[9)]	0.69	1	0.74	1	0.92	1	0.89	1	0.90	1	0.96	1
Share medium-sized firms[10)]	0.22	0	0.19	0	0.05	0	0.06	0	0.05	0	0.01	0
No. of firms	1,193		744		25,770		2,412		1,843		270,501	

Notes: The table shows mean and median values per firm-year in 2001-2018 by main industry. [1)] Mainland service industries, i.e., excluding petroleum-related services and shipping. [2)] All firms with applications in 1995-2018, operating during 2001-2018 (unbalanced panel). [3)] Firms with their *first* application in 2001-2018. [4)] No. of patent applications in a given firm-year in 2001-2018. [5)] Book value of total assets in NOK 1000 per employee. [6)] Value added in NOK 1000 per employee (10 NOK is appr. 1 EUR). [7)] Earnings before interest and taxes (EBIT) divided by the book value of total assets.[8)] Share of firm-years associated with firm age <=3 years. [9)] Share of firm-years by firms with less than 50 employees. [10)] Share of firm-years by firms with 50-250 employees.

Services. Moreover, the shares of start-up firms among first-time patenting firms in the two industries are 17 and 28 percent, respectively, compared to 12 and 22 percent among applicant firms. Thus, roughly 2-3 of 10 first-time patenting firms are start-ups. Start-ups as shares of overall firms are 21 and 30 percent for Manufacturing and Services, respectively.

3. Event study analysis

3.1. Regression model

To study the performance of firms before, during and after the first patent application, we use an event study setup. The dependent variable, *Y,* refers to one of the following: (i) log number of employees, (ii) log output (value added in NOK million),[9] (iii) log total assets, (iv) a dummy for whether the firm obtained public R&D support, (v) labor productivity (output per employee), and (vi) return on assets (profit divided by the book value of total assets, denoted RoA).

Let subscripts i and t refer to firm and year, respectively, and define τ_i as the first patent application year (possibly $\tau_i = \infty$). Then the regression equation for studying the effect of the patent event on Y_{it} is the following:

$$(1) \qquad Y_{it} = \sum_{j=-n}^{m} \beta_j 1_{(t-\tau_i=j)} + \gamma_{age(i,t)} + \lambda_{ind(i),t} + \nu_i + \varepsilon_{it}$$

where β_j is the parameter for having a patent application, n and m are the largest integers, such that $t-\tau_i = -n$ and $t-\tau_i = m$ for some $\tau_i \in \{2001, \dots, 2008\}$, $1_{(A)}$ is a dummy variable which is 1 if the statement A is true, and the mappings $age(i,t)$ and $ind(i)$ refer to the age interval (0-3, 4-9, 10-19 or ≥ 20 years) of firm-year (i, t) and the 2-digit NACE industry of

[9] NOK 100 $\approx$ EUR 10.

firm i, respectively. Finally γ_{age} represents a fixed age effect, $\lambda_{ind,t}$ a fixed time effect (specific to industry *ind*), v_i a fixed firm-effect, and ε_{it} the idiosyncratic error term.

A firm with a patent application whose first patent filing occurs at t (i.e., $\tau_i = t$) experiences a shift in Y_{it} equal to β_0, a shift in $Y_{i,t-1}$ equal to β_{-1}, a shift in $Y_{i,t-2}$ equal to β_{-2} and so on. Similarly, in the year following an application, there is a shift equal to β_1, then a shift equal to β_2 in the year after that, etc. All these shifts are relative to not having had *any* (published) patent applications.

We distinguish between two groups of firms: i) Firms without any patent applications (the potential *control group*), whose outcome variable, Y_{it}, fluctuates randomly around the trend $\gamma_{age(i,t)} + \lambda_{ind(i),t} + v_i$, and ii) firms with patent applications (the *treatment group*), which will then have a non-zero term $\beta_j 1_{(t-\tau_i=j)}$ for some value of j. The firm age dummies, $\gamma_{age(i,t)}$, are included to capture differences in firm dynamics between start-up firms, young firms and other firms. Firm age is potentially a confounding factor, because the dummy $1_{(t-\tau_i=0)}$ is expected to be negatively correlated with $age(i,t)$. Since the model includes a fixed effect (v_i) plus a common industry-specific trend ($\gamma_{age(i,t)} + \lambda_{ind(i),t}$), estimated values of β_j can be interpreted as "difference-in-differences" estimates.

3.2 Matching and balancing properties

We combine the event study design described above with matching. The purpose of matching is to control for confounding factors not captured by fixed effects and/or the age and industry dummies, i.e., (other) variables affecting both the propensity to patent and the outcome variable, Y_{it}. By so doing we attempt to mitigate endogeneity problems related to self-selection and facilitate a causal interpretation (see the discussion in Arkhangelski and Imbens, 2019; Blundell and Costa Dias, 2009; Heckman et al., 1997).

We match a treated firm – which submits its first patent application in $\tau_i \in \{2001, \ldots, 2018\}$ – with similar non-treated firms, i.e., firms with $\tau_i > 2018$. Note that we refer to all firms with a published patent application as "treated". We then estimate the regression models on the matched sample for $\tau_i \in \{2001, \ldots, 2018\}$, excluding all other firms. Specifically, our procedure is based on a vector of *discrete* stratification variables, *x,* which characterises the firm in a matching year prior to the first application:

x=(ind, age, empl, pubsupp),

where *empl* refers to an employment interval (0–4, 5–9, 10–49, 50–99, 100–249 or ≥ 250 employees) and *pubsupp* is a dummy for whether the firm obtained public R&D support in the given year. Each possible value of *x* corresponds to a specific cell. Within each cell, firms with patent applications are matched with firms without applications by means of propensity score matching, using log assets as a *continuous* matching variable.[10]

Our approach is in line with Lechner (2010) and Lechner and Wunsch (2013), who stress the importance of good balancing properties in the matched sample. In Table 2, we document the balancing properties after matching. Starting with the last row of Table 2, we observe that only about half of the first-time patenting firms of Table 1 are matched, i.e. included in Table 2. The non-matched firms either have no potential controls within their cell, or the quality of the propensity score match is not satisfactory (see footnote 10). The reduction in sample size in Table 2 compared to all first-time patenting firms in Table 1 is the price we pay for a matched sample with excellent balancing properties. None of the differences in mean values between the treated and control groups in Table 2 are significantly

[10] The matching procedure used is the STATA routine *psmatch2* with 1:5 nearest neighbour matching with trimming, where we retain the 5 best matches in the 5-year interval before the year of application for each treated firm. See Leuven and Sianesi (2010) for practical guidelines and technical details of the algorithm.

different from zero at the 5 per cent level.[11] In fact, the matched sample has good balancing properties with respect not only to the variables used in the matching, but also to the dependent variables *not* used in the matching (i.e., log labor productivity and RoA).[12]

Table 2. Balancing properties of the dependent variables and the matching variables in the year of matching, by main industry

	Manufacturing				Services			
	Treated[1)]		Control[2)]		Treated		Control	
Variable	Mean[3)]	SE[4)]	Mean	SE	Mean	SE	Mean	SE
Log no. of employees	2.54	0.20	2.54	0.27	1.56	0.24	1.58	0.17
Log output[5)]	8.68	0.32	8.51	0.32	7.52	0.32	7.50	0.24
Log assets	9.39	0.30	9.05	0.18	8.40	0.39	7.94	0.25
Log labor productivity[6)]	5.85	0.10	5.84	0.02	5.61	0.09	5.76	0.05
Return on assets (RoA)	0.05	0.02	0.05	0.01	0.02	0.02	0.06	0.01
Dummy of R&D support	0.35	0.11	0.35	0.10	0.34	0.13	0.34	0.13
Firm age	10.95	1.46	9.88	1.59	6.22	1.63	6.36	0.97
Share start-up firms[7)]	0.44	0.08	0.44	0.07	0.60	0.13	0.60	0.09
Share small firms[8)]	0.77	0.07	0.77	0.09	0.93	0.03	0.93	0.03
Share medium-sized firms[9)]	0.20	0.06	0.20	0.08	0.05	0.02	0.05	0.02
Total no. of firms	480		2,400		775		3,875	

Notes: Matched estimation sample. Mean values and standard errors (SE), by main industry. [1)] Firms that submit their *first* patent application in 2001-2018. [2)] Firms without any patent application matched to firms applying for patents by a combination of stratification and propensity score matching (1:5 matching). [3)] Weighted average across strata, with (frequency) weights equal to number of *treated* firms in each stratum. [4)] Clustered standard error by year of observation. [5)] Output measured as value added. [6)] Output per employee. [7)] Share of firms with age ≤ 3 years. [8)] Share of firms with less than 50 employees. [9)] Share of firms with 50-250 employees.

Comparing the characteristics of the matched firms in Table 2 and the first-time patenting firms in Table 1 reveals that the population of matched (first-time patenting) firms is younger and smaller (measured by number of employees) than the average first-time patenting firm in Table 1. For example, in Manufacturing the average log number of

[11] When the reported mean values are used with the standard errors to calculate 95 per cent (pairwise) confidence intervals for the treated and control groups for all the variables reported in the table, it is seen that they overlap. Formal tests of equality of *means* and *medians* are available from the authors upon request. In all cases, these tests lead to clear non-rejection.

[12] Note that the perfect balancing properties related to firm age and employment intervals and the dummy for public R&D support are an artifact of the stratification.

employees and share of start-ups in the matched sample are 2.54 and 44% respectively (see Table 2) vs. 2.7 and 12% among all first-time patenting firms (see Table 1). In Services, the corresponding figures are 1.56 (log employees) and 60% (share of start-ups) vs. 1.92 and 28%.[13] The share of small firms (less than 50 employees) is also slightly higher in the matched sample (Table 2) compared to all first-time patenting firms (Table 1): 77% vs. 74% in Manufacturing and 93% vs. 90% in Services. All these differences are related to the fact that Table 1 refers to averages across firm-years in the *period* 2001-2018, whereas Table 2 refers only to the matching *year* – which is 1-5 years prior to the patent event. In both Manufacturing and Services, about half of the firms in the matched sample are defined as start-ups (0-3 years old). Furthermore, the sample is dominated by small firms. We also see that approximately 1/3 obtained R&D support in the matching year.

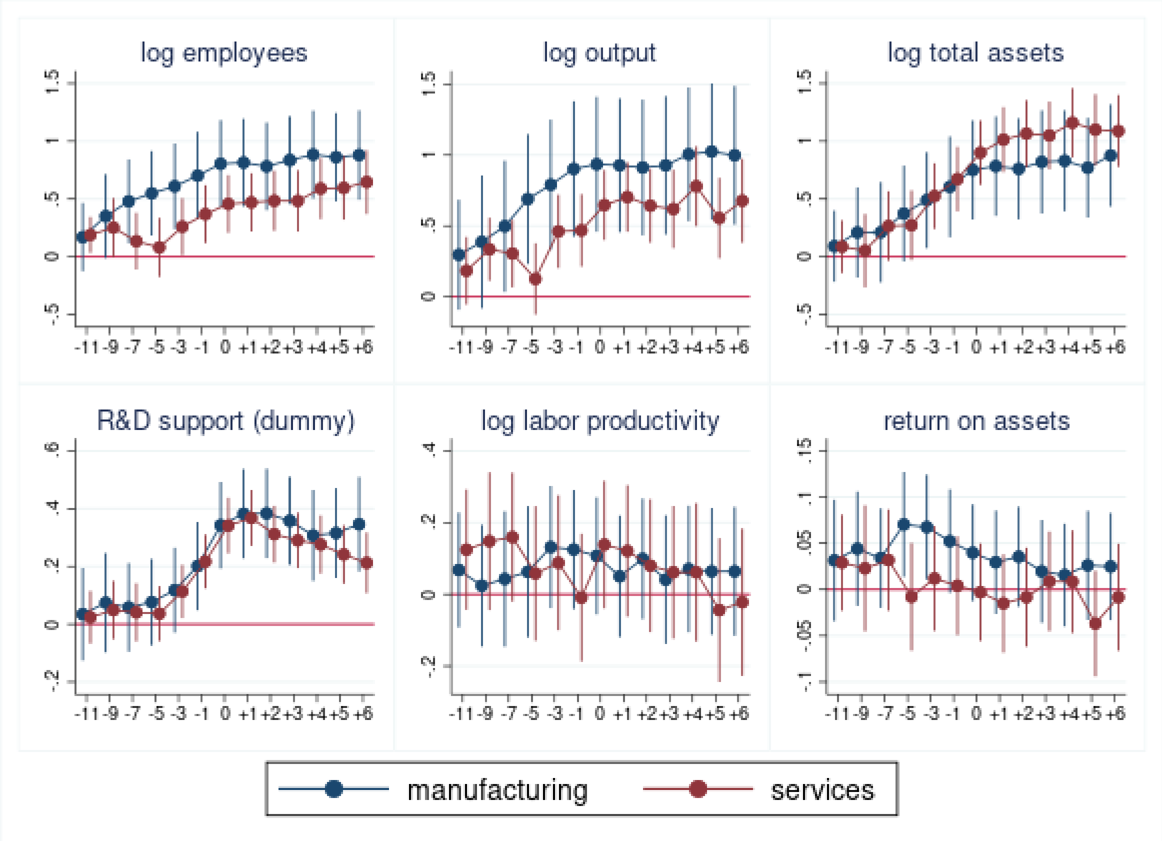
4. Empirical results

4.1. Estimated event effects

Below we present graphs of the fixed effects regression estimates $\hat{\beta}_j$ corresponding to the various variables (Y) of interest (see equation (1), where j refers to the number of years before/after the first patent application: if $j < 0$, $|j|$ refers to number of years *before*; if $j \geq 0$, j refers to number of years after. The graphs in Figure 3 illustrate how firms with patents in the Manufacturing and Service industries evolve from 11 years before the *first* application until 6 years after – relative to not having any patent applications at all.

[13] The average *number* of employees among first-time patenting firms in the matched sample is 48.5 in Manufacturing and 21.4 in Services compared to 66.7 and 24.5, respectively, among all first-time patenting firms in Table 1. These figures are highly sensitive to outliers, which is the reason our analyses focus on log levels, which are more symmetrically distributed and less influenced by extreme outliers (compare the mean and median in Table 1 for employment vs. log employment).

Figure 3. Plot of estimates of β_j of equation (1) vs. number of years since the application (*j*), with confidence intervals



Notes: The figure plots the estimates of β_j (the coefficients of equation (1)) vs. number of years since the application (*j*) for first-time patenting firms, with confidence intervals based on clustered (by firm) standard errors. A negative number on horizontal axis (*j<0)* refers to number of years before the first application, a non-negative number ($j \geq 0$*)* refers to number of years after the first application.

We start with a sample for which there is initially (either in 2001 or in the firm's founding year) no *previous* patent application. Thus, we focus here on what we refer to as the extensive margin, i.e. going from zero to a positive number of applications. Then we measure the evolution of the variables relative to the year when the first patent application is filed. The variable on the horizontal axis is: $t - \tau_i$. Thus, 0 refers to the year of the first patent application. At first sight, there are several highly significant coefficients displayed in Figure 3, implying that a patent affects firms' employment, output and total assets alike. The magnitudes of the corresponding coefficients are large – indicating persistently increased levels following the application compared to 11 years previously. We also observe that developments for Manufacturing and Services are very similar, probably reflecting the fact that first-time patenting firms have quite similar characteristics across industries (see Tables 1-2).

The results show that employment, output and total assets start to increase significantly *at least* three years before the patent application in both industries. For all these variables, the level is in the range of 0.2 – 0.8 higher on a logarithmic scale three years before the patent filing compared to what would have been the case without the patent. 5-6years after the application, the estimated effects are in the range of 0.6 to 1.1 on a logarithmic scale. The largest effect is seen for total assets.

The increase in the probability of obtaining public R&D support is of the same order of magnitude as the effect on growth in employment, output and total assets. We estimate a 20-30 p.p. increase in the probability of obtaining public R&D subsidies 5-6 years after the patent event compared to having zero patent applications. This probability reaches its highest level in the interval from one year before (-1) to one year after the application (+1), and then drops over the next three years. These findings mean that there is a positive relation between closeness to the time of patenting and the probability of obtaining public support.

In stark contrast to the above findings, the ratio variables, i.e., labor productivity and return on assets, are not affected by the patent application, as evident from the fact that all coefficients are statistically insignificant. This may indicate that the profitability and productivity implications of patenting may take a long time to materialize. Seemingly in contrast to our results, Bloom and van Reenen (2002) find that total factor productivity increased by (a modest, but significant) 3 percent due to a doubling of citation-weighted patents.[14] However, citation weighting means that estimates are clearly hampered by a positive bias, as successful, long-lived patents will receive more citations and therefore a higher weighting.

[14] Their sample covers 236 (mainly) large, British firms accounting for 59,919 patents between 1968 and 1996.

Supplementary results are shown in Table 3, where we report smoothed (3-year moving-average) parameter estimates: $\tilde{\beta}_j = (\hat{\beta}_{j-1} + \hat{\beta}_j + \hat{\beta}_{j+1})/3$ corresponding to log employment, log output, log assets and the dummy *pubsupp*. As already seen from Figure 3, all the estimated effects become significantly positive at the 5 percent level 3-9 years before the patent application is filed. All estimated effects remain highly significant at least 6 years after the application year, with p-values <0.001. For employment, output and total assets, the patent event has a huge effect: over a 10-year period from 5 years *before* the first application to 5 years after, the average annual growth rate of a first-time patent applicant is 3-5 p.p. higher than that of a matched control group, and there are no signs of a mean reversion 5-6 years after the event. The likelihood of obtaining public R&D support also stabilizes at a significantly higher level 5-6 years after the application compared to 5 years before.

In the case of both Manufacturing and Services, we find that the estimated effects are largest in the years subsequent to the patent application. Moreover, the effects are already present – and increasing – in a 5-year period prior to the application date. One possible explanation is that the findings reflect self-selection, rather than causal effects. However, this problem should be mitigated by the matching. First, as shown in Section 3.2, the balancing quality of the matching was excellent with respect to the matching variables in x, which are confounding factors because they are related to firm performance – either directly or indirectly through market and life-cycle conditions. The matching also addresses the fact that patenting firms are concentrated in certain industries and tend to be relatively small and young. Second, as shown in Table 2, we have excellent balancing properties also with respect to RoA and labor productivity, even though these variables were not used in the matching. Third, we control for selection on time-invariant unobservables through the inclusion of fixed effects. Such time-invariant characteristics could for instance be entrepreneurial and managerial qualities (see e.g. Custodio et al., 2017). The combination of matching and different types of fixed effects should insulate our results from simply reflecting self-selection.

4.2. Robustness

In Table A.1 in the Appendix, we investigate the robustness of the results reported in Table 3 with respect to the number of nearest neighbors used in the matching. In Table A.1 we use 1:2 matching – retaining the 2 best matches in the 5-year interval before the year of application for each treated firm – instead of 1:5 matching (used in Table 3, see footnote 10). Overall, the conclusions with respect to the timing, significance and magnitude of the estimates remain unchanged, although the estimated effects are generally more moderate in Table A.1 compared to Table 3. For example, with respect to employment, output and total assets, we estimate that the level of these variables is in the range of 0.1 – 0.5 higher on a logarithmic scale three years before the patent filing compared to what would have been the case without the patent. Five-six years after the application, the estimated effects are in the range of 0.2 to 0.8 on a logarithmic scale, but with a tendency of stronger and more significant effects in Manufacturing than in Services. Further, we estimate a highly significant 15-20 p.p. increase in the estimated probability of obtaining public R&D subsidies 5-6 years after the patent event.

With respect to the choice of matching variables, the results are most strongly affected by the exclusion of the variable *pubsupp* – the dummy for the receipt of public R&D support. If this variable is not used in the matching, the estimated effects become higher than reported in Table 3 or Table A.1.[15] This variable is a proxy for a firm's prior R&D and innovation efforts, which potentially affect both firm performance and the propensity for patenting. For example, without controlling for *prior* R&D, we risk confounding the effect of conducting R&D with the effect of patenting.

[15] We do not report the corresponding results here, which are available from the authors upon request.

Table 3. Three-year moving averages of effect parameters (equation (1))

Parameter	Manufacturing								Services							
	Log empl.		Log output		Log assets		Pubsupp		Log empl.		Log output		Log assets		Pubsupp	
	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.
β_{-10}	0.270	0.095	0.338	0.097	0.144	0.386	0.069	0.351	0.216	0.045	0.245	0.010	0.016	0.902	0.033	0.425
β_{-9}	0.365	0.038	0.428	0.048	0.226	0.220	0.091	0.232	0.205	0.100	0.270	0.007	0.021	0.887	0.056	0.226
β_{-8}	0.428	0.019	0.484	0.035	0.253	0.211	0.078	0.310	0.182	0.139	0.299	0.005	0.141	0.330	0.060	0.212
β_{-7}	0.481	0.009	0.555	0.016	0.302	0.144	0.086	0.249	0.137	0.271	0.259	0.020	0.267	0.067	0.073	0.129
β_{-6}	0.514	0.005	0.596	0.009	0.315	0.132	0.078	0.294	0.111	0.375	0.215	0.053	0.324	0.022	0.055	0.230
β_{-5}	0.550	0.003	0.673	0.003	0.367	0.077	0.102	0.164	0.116	0.363	0.195	0.097	0.372	0.009	0.083	0.064
β_{-4}	0.583	0.002	0.736	0.002	0.411	0.049	0.108	0.136	0.164	0.190	0.278	0.021	0.403	0.005	0.091	0.039
β_{-3}	0.619	0.001	0.756	0.001	0.467	0.026	0.146	0.044	0.238	0.056	0.390	0.001	0.517	0.000	0.147	0.001
β_{-2}	0.657	0.001	0.815	0.001	0.546	0.011	0.170	0.022	0.311	0.012	0.464	0.000	0.605	0.000	0.178	0.000
β_{-1}	0.722	0.000	0.863	0.000	0.633	0.004	0.245	0.001	0.376	0.003	0.526	0.000	0.730	0.000	0.254	0.000
β_{0}	0.774	0.000	0.922	0.000	0.714	0.001	0.309	0.000	0.432	0.001	0.606	0.000	0.862	0.000	0.309	0.000
β_{1}	0.801	0.000	0.925	0.000	0.765	0.001	0.369	0.000	0.471	0.000	0.664	0.000	0.993	0.000	0.340	0.000
β_{2}	0.811	0.000	0.922	0.000	0.789	0.000	0.374	0.000	0.480	0.000	0.655	0.000	1.043	0.000	0.323	0.000
β_{3}	0.834	0.000	0.948	0.000	0.804	0.000	0.349	0.000	0.520	0.000	0.681	0.000	1.092	0.000	0.292	0.000
β_{4}	0.861	0.000	0.986	0.000	0.807	0.000	0.327	0.000	0.557	0.000	0.651	0.000	1.103	0.000	0.269	0.000
β_{5}	0.876	0.000	1.010	0.000	0.826	0.000	0.323	0.000	0.611	0.000	0.671	0.000	1.116	0.000	0.243	0.000
β_{6}	0.902	0.000	1.064	0.000	0.870	0.000	0.326	0.000	0.607	0.000	0.648	0.000	1.099	0.000	0.214	0.000

Note: The table shows the three-year moving averages $\tilde{\beta}_j = (\hat{\beta}_{j-1} + \hat{\beta}_j + \hat{\beta}_{j+1})/3$ of the regression results depicted in Figure 3. p-values based on robust standard errors (clustered by firm). The matched estimation sample is obtained by 1: 5 nearest neighbour matching, where we retain the 5 best matches in the 5-year interval before the year of application for each treated firm.

4.3. Relation to existing literature

Our results indicate that a published patent application has economic impact well ahead of the application date. This is not surprising, because firms develop ideas as a part of their daily business, not in an intellectual vacuum. The real economic implications of patenting, for both investment in tangible capital and the hiring and training of workers, were highlighted by Bloom and van Reenen (2002) in the context of a neo-classical model. However, we find that the effects start to show several years before the filing of patent applications, spurring economic growth along the way. Our results demonstrating large returns on patenting with respect to a wide set of (economies-of-scale) variables before the application date constitute a novel contribution to the literature.

Our results contrast strikingly with those of Farre-Mensa et al. (2020), who find huge positive returns in a five-year period *after* the "first-action date", which typically is around the time of publication (1-2 years after the application date). For example, in terms of employment and sales growth they find that first-time patenting firms experience 55 and 80 p.p. higher 5-year growth than "unsuccessful applicants" (which means that a patent is not granted within their observation window). In comparison, our estimates of additional growth in the treatment group relative to the control group are in the range of 0-15 p.p. over the 5-year interval from +1 to +6 and barely significant (see Figure 3 and Table 3). Of course, these two sets of results are not directly comparable, as Farre-Mensa et al. *op. cit.* compare successful applications with unsuccessful ones (first-time applications that are not approved). We would expect that if we were to compare approved applications with non-approved ones on our data, mimicking the analysis of Farre-Mensa et al., we might get uniformly *lower* diff-in-diff estimates than those reported in Table 3. The reason is that a published application –

even if it does not lead to an IPR – should be of economic value to the firm.[16] The expectation is generally confirmed by the following diff-in-diff-in-diff analysis: First, we estimated the effect of having an *approved* first-time patent application vs. a matched control group of non-applying firms, using the same methodology as described in Section 3. Second, we did the same (diff-in-diff) analysis on *non-approved* first-time applicants vs. a control group of non-applying firms. Third, we took the pairwise differences between the two sets of estimates. In this way, we found uniformly positive (diff-in-diff-in-diff) estimates in the interval -10 to +6, as reported in Table A.2 in the appendix. As expected, the estimates in Table A.2 are lower than in Table 3. More importantly, the diff-in-diff-in-diff estimates are never significant at the 5 percent level until we reach the sub-interval from +1 to +6 years, where *some* of them are associated with p-values in the range of 1 – 5 percent. The estimated additional growth in employment, output and total assets from year +1 to year +6 is in the range of 10-20 p.p., which is much lower than the (comparable) 55-80 p.p. additional growth estimated by Farre-Mensa et al. (2020).

We cannot interpret the results in Table A.2 as unbiased estimates of the *incremental* value of the IPR *per se*, i.e. above the value of the underlying innovation. The reason is that self-selection means that the most valuable patent applications are likely to be approved, whereas the least valuable ones may simply be abandoned by the applicant. This causes a positive correlation between patent approval and patent quality, and a positive bias in the (diff-in-diff-in-diff) estimates reported in Table A.2 (e.g. from year +1 to +6). Therefore, being upward-biased, the estimates in Table A.2 cast doubt on the plausibility of the huge additional value of the IPR (above the value of the innovation itself) estimated by Farre-Mensa et al. (2020).

[16] For example, a firm could obtain a competitive advantage by publishing a patent application even if an IPR was not granted (see Ziedonis, 2004).

4.4 Life-cycle dynamics

Table 4. Estimated coefficients of control variables related to firm age

		Manufacturing		Services	
Dependent variable	Age interval[1)]	Estimate	t-value[2)]	Estimate	t-value
Log employment	4-9 years	0.17	26.5	0.19	17.2
	10-19 years	0.24	24.0	0.28	16.3
	>19 years	0.24	16.0	0.30	12.2
Log output	4-9 years	0.32	31.9	0.32	19.9
	10-19 years	0.38	25.2	0.42	16.5
	>19 years	0.32	14.4	0.40	10.8
Log total assets	4-9 years	0.32	34.5	0.31	21.2
	10-19 years	0.41	29.4	0.42	18.9
	>19 years	0.36	18.4	0.42	13.5
Public R&D support (dummy)	4-9 years	0.01	3.2	0.01	1.4
	10-19 years	0.00	1.0	0.00	0.3
	>19 years	0.00	0.4	0.00	0.5
Log labor productivity	4-9 years	0.14	23.8	0.12	13.6
	10-19 years	0.12	15.2	0.10	8.5
	>19 years	0.08	7.2	0.09	4.9
Return on assets	4-9 years	0.02	10.0	0.01	4.1
	10-19 years	0.02	6.1	0.01	2.3
	>19 years	0.01	2.3	0.00	0.4

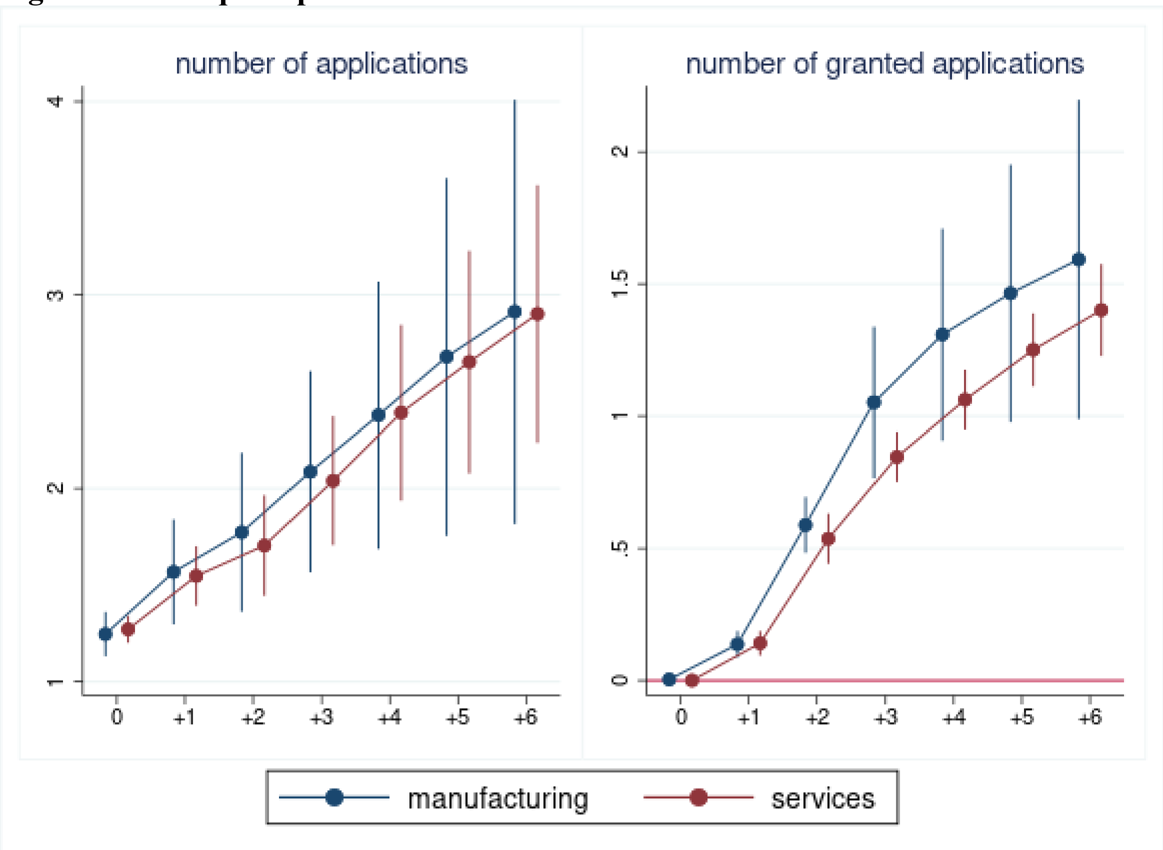
[1)] Reference category is start-up firms (firm-age $\leq$ 3 years). [2)] From robust standard errors (clustered by firm).

In Table 4 we report the estimated age-dummy coefficients from the regression analyses. The age dummies are control variables representing life-cycle dynamics, with start-up firms as the reference category. From Table 4 we observe that all the coefficient signs are the same for Manufacturing and Services, and that they are all positive and highly significant except the coefficients related to public R&D support, which are never significant. The estimated relations between Age interval, on the one hand, and Log employment and Log output, on the other, are not surprising. Older firms have, on average, more employees and larger output. Start-up firms have significantly lower productivity than incumbent firms, with highest productivity in the age category 4-19 years. This finding is in line with Brasch and Raknerud (2022). Likewise, profitability depends on firm age, with firms aged between 4 and 19 years being the most profitable. Start-up firms are, not surprisingly, the least profitable firms on average.

4.5 Subsequent patent activities

In the above we examined the effects of the first patent application on a set of outcome variables. It might also be of interest to investigate the extent of patent activities subsequent to the first application. To do so, we consider both the number of applications and the number of approved (i.e., granted) patents. The latter may refer to either first-time or later application(s). The left panel of Figure 4 shows that the average number of applications (≥ 1) at time 0 (the year of the first application) is 1.2. Some firms file additional applications in subsequent years. Thus, 6 years after the first application, the average number of applications per firm is close to 3, regardless of industry. The right panel of Figure 4 shows that there are zero *approved* applications at time 0, reflecting the time lag between the date of an application and the date of it being granted. The numbers of approved applications 3 and 6 years after the first application (including any approved subsequent applications) average about 1 and 1.5, respectively. These figures indicate that repeated patenting is common and could be one of the reasons for the *persistent* positive findings reported in Section 4.1. However, the flat pattern of size-related outcome variables (employment, output and assets) after the first application in Figure 3, indicates that the additional growth impulses related to subsequent patents are weak compared to those generated by the first one. These findings are consistent with those in Farre-Mensa et al. (2020), who find that repeated patenting is widespread, but that the economic returns on later patents are small. Our findings are also in line with evidence of an inverse relation between the economic impact of innovations and the experience of entrepreneurs (Lahiri and Wadhwa, 2001). We conclude that patenting is particularly important early in the life cycle of a firm, i.e. more important on the extensive than on the intensive margin.

Figure 4. Subsequent patent activities



Note: The figure plots the estimates of β_j coefficients related to the number of applications and granted patents. Number of years after first application (j) on horizontal axis.

5. Concluding remarks

Given the increasing importance of investment in business enterprise R&D in modern economies, it is important to increase our knowledge of the impact of firms' R&D and innovation activities. In this study we do so by utilizing the whole population of Norwegian limited liability firms followed from 2001 to 2018 and use micro-econometric methods to investigate their behavior before, during and after their *first* patent application. Our data allow us to follow a large treatment group and to form a control group using a matching technique.

Through matching we control for a set of confounding factors, i.e., variables affecting both propensity to patent and outcome variables. Statistical matching combined with fixed effects panel data modeling, enables us to interpret parameters as representing the causal effect of innovation – as opposed to merely reflecting confounding factors, e.g. prior R&D activity or economic performance.

We find that first-time patenting firms experience an increase in economic activity, measured by employment, output, and asset growth, as well as the likelihood of securing public R&D support. The effect starts at least 3 years before the filing of the patent application and persists until at least 6 years after the application date. Our results, which show early returns to patenting with respect to several (economies-of-scale) variables, represent a novel contribution to the literature, which recently has focused more on the importance of information disclosure (Hegde and Luo, 2018) or the value of patent approval *per se* (Farre-Mensa et al., 2020). We find no evidence of a large incremental value *after* patent approval for successful applicants, which casts doubt on some findings in the recent literature. Moreover, our results indicate that additional growth impulses related to subsequent patents are weak compared to the first one.

Our results support the view that there is a significant positive link between patents and economic growth early in the life cycle of a firm. Such findings are in line with many studies of the impact of R&D subsidies. For instance Nilsen et al. (2020) find that public R&D support has significant effects, mainly on the extensive margin and less so on the intensive one. The present study indicates that the existence of a properly functioning patenting system supports innovation activities and is therefore important.

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Appendix A.

Table A.1. Three-year moving averages of effect parameters (equation (1)) with 1:2 matching

Parameter	Manufacturing								Services							
	Log empl.		Log output		Log assets		Pubsupp		Log empl.		Log output		Log assets		Pubsupp	
	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.
β_{-10}	0.178	0.062	0.205	0.072	0.098	0.324	0.010	0.816	0.137	0.068	0.216	0.014	0.114	0.295	-0.009	0.728
β_{-9}	0.238	0.018	0.259	0.029	0.148	0.167	0.036	0.402	0.110	0.178	0.195	0.035	0.065	0.581	0.002	0.937
β_{-8}	0.266	0.010	0.297	0.018	0.163	0.159	0.025	0.565	0.079	0.342	0.146	0.130	0.121	0.309	0.005	0.860
β_{-7}	0.274	0.011	0.336	0.009	0.193	0.109	0.024	0.577	0.059	0.495	0.098	0.333	0.196	0.108	0.027	0.380
β_{-6}	0.292	0.007	0.373	0.005	0.215	0.080	0.023	0.594	0.046	0.607	0.055	0.598	0.252	0.039	0.026	0.389
β_{-5}	0.320	0.004	0.431	0.001	0.261	0.035	0.053	0.213	0.050	0.591	0.085	0.433	0.268	0.030	0.047	0.110
β_{-4}	0.350	0.002	0.487	0.000	0.291	0.021	0.071	0.094	0.064	0.490	0.169	0.124	0.296	0.018	0.058	0.045
β_{-3}	0.388	0.001	0.510	0.000	0.323	0.012	0.107	0.012	0.113	0.224	0.247	0.027	0.384	0.002	0.093	0.001
β_{-2}	0.424	0.000	0.545	0.000	0.383	0.004	0.129	0.003	0.167	0.076	0.305	0.007	0.500	0.000	0.130	0.000
β_{-1}	0.480	0.000	0.595	0.000	0.473	0.000	0.183	0.000	0.218	0.022	0.337	0.003	0.638	0.000	0.199	0.000
β_{0}	0.518	0.000	0.648	0.000	0.562	0.000	0.230	0.000	0.249	0.010	0.391	0.001	0.746	0.000	0.252	0.000
β_{1}	0.540	0.000	0.667	0.000	0.598	0.000	0.256	0.000	0.258	0.009	0.399	0.001	0.817	0.000	0.270	0.000
β_{2}	0.535	0.000	0.643	0.000	0.602	0.000	0.245	0.000	0.247	0.013	0.367	0.002	0.819	0.000	0.247	0.000
β_{3}	0.543	0.000	0.629	0.000	0.574	0.000	0.212	0.000	0.250	0.014	0.352	0.004	0.820	0.000	0.213	0.000
β_{4}	0.552	0.000	0.631	0.000	0.562	0.000	0.191	0.000	0.266	0.010	0.286	0.021	0.806	0.000	0.195	0.000
β_{5}	0.568	0.000	0.651	0.000	0.571	0.000	0.180	0.000	0.283	0.008	0.276	0.030	0.800	0.000	0.175	0.000
β_{6}	0.581	0.000	0.710	0.000	0.617	0.000	0.172	0.000	0.265	0.014	0.213	0.102	0.758	0.000	0.153	0.000

Note: The table shows the three-year moving averages $\tilde{\beta}_j = (\hat{\beta}_{j-1} + \hat{\beta}_j + \hat{\beta}_{j+1})/3$. p-values based on robust standard errors (clustered by firm). The matched estimation sample is obtained by 1:2 nearest neighbour matching. P-values are based on robust standard errors (clustered by firm).

Table A.2. Diff-in-diff-in-diff estimates of the effect of approved vs. non-approved first-time applications

Parameter	Manufacturing								Services							
	Log empl.		Log output		Log assets		Pubsupp		Log empl.		Log output		Log assets		Pubsupp	
	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.
β_{-10}	0.127	0.525	0.022	0.894	0.075	0.727	0.091	0.302	0.149	0.375	0.022	0.894	-0.234	0.261	0.088	0.111
β_{-9}	0.175	0.408	0.097	0.580	0.113	0.625	0.079	0.383	0.173	0.315	0.097	0.580	-0.141	0.531	0.108	0.066
β_{-8}	0.230	0.292	0.258	0.162	0.127	0.608	0.073	0.434	0.190	0.315	0.258	0.162	0.008	0.973	0.111	0.064
β_{-7}	0.320	0.153	0.260	0.178	0.171	0.503	0.089	0.335	0.139	0.226	0.260	0.178	0.108	0.647	0.091	0.133
β_{-6}	0.341	0.129	0.242	0.225	0.153	0.553	0.072	0.429	0.110	0.203	0.242	0.225	0.097	0.682	0.057	0.344
β_{-5}	0.351	0.121	0.119	0.565	0.165	0.522	0.049	0.585	0.103	0.158	0.119	0.565	0.141	0.558	0.066	0.260
β_{-4}	0.341	0.135	0.095	0.649	0.197	0.451	0.018	0.844	0.160	0.147	0.095	0.649	0.141	0.560	0.063	0.271
β_{-3}	0.329	0.153	0.151	0.473	0.257	0.331	0.015	0.869	0.198	0.166	0.151	0.473	0.198	0.402	0.102	0.073
β_{-2}	0.327	0.161	0.173	0.417	0.305	0.257	0.014	0.874	0.230	0.129	0.173	0.417	0.129	0.582	0.083	0.147
β_{-1}	0.343	0.145	0.232	0.282	0.296	0.281	0.059	0.516	0.248	0.142	0.232	0.282	0.077	0.743	0.092	0.122
β_{0}	0.367	0.123	0.252	0.248	0.272	0.328	0.094	0.305	0.280	0.133	0.252	0.248	0.099	0.675	0.094	0.121
β_{1}	0.364	0.126	0.321	0.145	0.290	0.301	0.169	0.066	0.326	0.174	0.321	0.145	0.194	0.417	0.129	0.035
β_{2}	0.395	0.096	0.333	0.133	0.324	0.253	0.202	0.031	0.355	0.127	0.333	0.133	0.263	0.274	0.142	0.020
β_{3}	0.433	0.069	0.431	0.055	0.420	0.138	0.221	0.020	0.440	0.063	0.431	0.055	0.344	0.158	0.154	0.012
β_{4}	0.479	0.046	0.496	0.029	0.453	0.108	0.216	0.024	0.481	0.035	0.496	0.029	0.382	0.122	0.140	0.025
β_{5}	0.476	0.049	0.547	0.019	0.473	0.092	0.232	0.016	0.564	0.034	0.547	0.019	0.420	0.091	0.121	0.062
β_{6}	0.493	0.043	0.592	0.012	0.469	0.012	0.246	0.010	0.575	0.040	0.592	0.012	0.474	0.060	0.095	0.146

Note: The table shows difference between estimates $\tilde{\beta}_{1j} - \tilde{\beta}_{0j} = (\hat{\beta}_{1,j-1} - \hat{\beta}_{0,j-1} + \hat{\beta}_{1,j} - \hat{\beta}_{0,j} + \hat{\beta}_{1,j+1} - \hat{\beta}_{0,j+1})/3$, where $\tilde{\beta}_{1j}$ refers to estimates of parameters in the model for approved applications and $\tilde{\beta}_{0j}$ to non-approved application. The matched estimation samples are obtained by 1:5 nearest neighbour matching. P-values are based on robust standard errors (clustered by firm).