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Science parks: seedbeds of innovation? A duration analysis of firms' patenting activity

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Abstract This article investigates the role of Science Parks (SPs) as seedbeds of innovation. It aims to verify if and to what extent firms' innovative performance is affected by relocating inside a SP. The analysis is structured in the form of a duration model that holds patenting as a repeated and event-dependent phenomenon and accounts for the persistence of innovative activities and the cumulativeness of knowledge. Estimates are based on a conditional risk-set model. The study relies on an original database regarding Finnish SPs: 252 firms that in the year 2002 were located in the Parks and the firms' lifetime patenting activity, over a 33-year-period. We find support for the existence of spillovers and for the positive role of incubators over those firms joining SPs when very young.

Keywords Duration analysis · Innovation · Knowledge spillovers · Patents · Science Parks · Seedbeds of innovation

JEL Classifications C410 · L250 · O310 · L26

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1 Introduction

This article investigates the role of Science Parks (SPs) as seedbeds of innovation. It aims to verify if and to what extent firms' innovative performance, measured in terms of patents, is affected by the event of relocating inside the SPs. The analysis is structured in the form of a duration model that holds patenting as a repeated and event-dependent phenomenon and accounts for the persistency of innovative activities (Cefis 2003) and the cumulativeness of knowledge. The study relies on an original database that regards the Finnish SPs, 252 firms that in the year 2002 were located on SP premises, and these firms' lifetime patenting activity. The data span a 33-year-period, from January 1970–December 2002, and is recorded on a daily basis.

Our analysis of the Finnish SPs both contributes to and relies upon the empirical literature on SPs that aims to assess the effectiveness of these innovation policy instruments. It also incorporates further insights offered by the literature on innovation and patents, on knowledge and knowledge spillovers, and on firm characteristics and innovativeness, including the Product Life Cycle (PLC) literature.[1] By focusing on Finland, we shed some light on a still unexplored SP experience and on the innovation dynamics of a country whose competitiveness has substantially

[1] The econometric literature is dealt with in the econometric model section.

increased over the last two decades, mainly thanks to the creation and exploitation of new knowledge and technologies.

In order to empirically verify if SPs succeed in constituting seedbeds of innovation, we investigated the innovative activity of a sample of firms that were originally established outside the Parks and that, at a certain moment in their lifetime, moved inside the SPs. The duration model we estimate evaluates and compares the innovative performance that firms exhibit before joining the SPs (what we call the 'before' period) with that shown after becoming SP tenants (i.e. the 'after' period). Our analysis, which basically is a 'before VS after' test, aims to check if and to what extent locating inside the SPs makes companies more likely to innovate than they were before entering the Parks.

The innovativeness of the firms is measured by means of their patenting activity, as patents represent a fairly standardised output measure and a detailed source of data (Griliches 1990). Our patent-based analysis also accounts for the behaviour of some of the most important variables known to influence companies' innovative activity, in particular firm characteristics (see, among others, Scherer 1984; Schankerman and Pakes 1986; Jaffe and Trajtenberg 2002).

The structure of the article is as follows. Section 2 reviews the SPs literature. Section 3 presents the data collection methodology and some descriptive statistics. Section 4 illustrates the duration model (Sect. 4), its main features (Sect. 4.1), the econometrics (Sect. 4.2) and the hypotheses that we make (Sect. 4.3). Section 5 presents the estimates, whereas results are discussed in Sect. 5.1. Section 6 shows some robustness checks and we finally conclude in Sect. 7.

2 A review of the Science Parks literature

SPs are organizations that should bridge research and industry and thus promote the innovativeness and competitiveness of their associated businesses and knowledge-based institutions (IASP 2002; OECD 1997). To this end SPs should, among other tasks, facilitate the flow of knowledge and technology between universities, R&D institutions and companies, and support new technology-based firms (NTBFs). Over time, the remarkable growth in importance and the diffusion of these multi-sponsor multi-objective organizations has motivated many to investigate the Parks' performance and value-added. Among these studies we find those Hodgson (1996) defines as 'relative performance' and 'impact evaluation' analyses, i.e. assessments focusing on the links between SPs' activities and related outcomes. These analyses put under scrutiny aspects like R&D, innovation input and innovation output; the survival and growth of NTBFs; the establishment of links with Higher Education Institutions (HEIs); agglomeration effects; and regional growth (see Table 1).

Monck et al's study (1988) pioneers the SPs assessment tradition by investigating the extent to which UK SPs add value to businesses. To this end the authors construct a first-hand survey-based dataset of high-technology firms located in and out the SPs, database later updated and used in many UK studies. Monck et al. (1988) and the other UK-based analyses use quite an array of measures to asses SPs' value added. Among them the launch of new products and services, SPs firms' R&D intensity, tendency to patent, outturn measures, survival/closure rates, links with HEIs, and SPs' ability to constitute seedbeds for NTBFs. Overall evidence is mixed with respect to SPs' effectiveness and the results do not corroborate or disprove the hypothesis that UK SPs successfully accomplish their policy mission.

A group of more recent Swedish studies pictures SPs as being somewhat more successful, but results are not clear-cut either. On the one hand, Löfsten and Lindelöf (2001) and Lindelöf and Löfsten (2003) find the Park milieu to have a positive impact on the tenants' growth, in terms of both sales and employment. On the other hand though, Ferguson and Olofson (2004) deem these same differences to be insignificant. With respect to establishing links with HEIs, in-SP NTBFs are found more likely than out-of-Park firms to do so (Löfsten and Lindelöf 2002; Lindelöf and Löfsten 2004), but no significant differences emerge in the profitability of in-SP NTBFs versus out-SPs ones (Löfsten and Lindelöf 2005).

Colombo and Delmastro's (2002) analysis of Italian NTBFs located in and out the SPs instead supports the view that SPs are important technology policy tools, especially in countries where national innovation systems are weak. Among other results, they find in-SP NTBFs to perform comparatively

Table 1 SPs' Relative performance and impact evaluation studies

Author(s)	Country	Period analysed	Publication year
Monck, Porter, Quintas, Storey, and Wynarczyk	UK	1986	1988
Massey, Quintas and Wield	UK	1986, 1990	1992
Westhead and Storey	UK	1986, 1992	1994, 1995
Westhead	UK	1986, 1992	1997
Siegel, Westhead and Wright	UK	1992	2003
Felsenstein	Israel	–	1994
Luger and Goldstein	US	1989	1991
Link and Scott	US	2001	2003
Link and Scott	US	1950–2002	2006
Appold	US	1960–1985	2004
Löfsten and Lindelöf	Sweden	1994–1996	2001
Löfsten and Lindelöf	Sweden	1999	2002, 2003, 2005
Lindelöf and Löfsten	Sweden	1999	2004
Dettwiler, Lindelöf and Löfsten	Sweden	1999	2006
Ferguson and Olofsson	Sweden	1995, 2002	2004
Colombo and Delmastro	Italy	2000	2002
Chen, Wu and Lin	Taiwan	1991–1999	2006
Fukugawa	Japan	2001–2003	2006

Source: Squicciarini (2007)

better in terms of adoption of new technologies, growth rates and the establishment of collaborative agreements and links with HEIs. This last result also emerges from Fugukawa's (2006) analysis of Japanese NTBFs located in and out the SPs.

The US SPs' literature adds further interesting elements to the discussion on SP effectiveness by shifting the focus of the analysis from the firms to the SPs themselves. Luger and Goldstein (1991) investigate the rate at which Parks foster the creation of new jobs at the regional level and classify SPs according to their success/failure. Link and Scott (2003, 2006) look at the diffusion and growth of the US SPs themselves and, among other results, find that those Parks located closer to universities, operated by private organisations and having specific technology foci grow faster than the average. Appold (2004) instead analyses SPs' ability to affect the growth (in number) of local laboratories. His findings question the cause–effect link initially hypothesised, and he concludes that SPs benefit from the growth of the research activities carried out in the area rather than constituting effective local development tools.

From the short survey above, one sees that evidence about SPs' effectiveness is mixed. Results do not allow to argue in favour of or against these innovation policy tools, or to assess their value added vis-à-vis that of other instruments, but rather suggest to further study SPs. The present article does so by focusing on the relationship between locating inside a SP and the innovation activity of the firms. The idea to investigate the role of SPs as seedbeds of innovation, which was first proposed by Felsenstein (1994), is in our case motivated by the very rationale behind the creation of SPs. SPs were in fact initially conceived as innovation and competitiveness enhancing regional policy tools. Emphasis is on innovation because higher innovative outputs are held to be positively correlated with firms' productiveness (Crépon et al. 1998) and competitiveness.

SPs represent milieus where geographical proximity should allow firms to importantly benefit from R&D and knowledge spillovers. SPs should in fact accomplish their policy mission by opportunely managing and channelling the knowledge and knowledge spillovers generated within their premises, as these represent the most important determinants of innovation. However, not all types of spillovers favour innovation. The lack of appropriability that outgoing spillovers (Cassiman and Veugelers 2002) determine may counterbalance the positive effect that

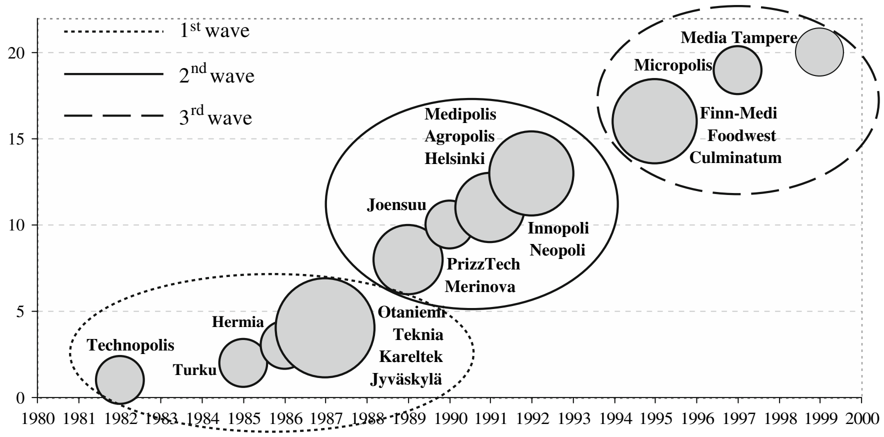

Fig. 1 Finnish science parks by year of creation (Data regarding 20 out of 21 Science Parks (Kajaani excluded). The size of the circles is proportional to the number of Science Parks established in the year considered)

the diffusion of knowledge may have on innovation. Spillovers will, therefore, ultimately favour or hinder innovation depending upon which of the two effects is predominant (e.g. Katz 1986; Aghion and Tirole 1994; Klette 1996; Sena 2004). This in turn depends—also although not exclusively—on the channels through which spillovers work. Particularly important in this respect is geographical proximity (e.g. Audretsch and Feldman 1996; Henderson et al. 1995; Feldman and Audretsch 1999). It thus become evident the rationale behind the creation of SPs: building physical loci where facilitating industry—research links and opportunely managing knowledge flows, in an attempt to foster the innovativeness of the SP tenants.

3 The data

Our analysis is based on first-hand data, collected in the year 2002. The data regard the Finnish SPs, a sample of firms that in the year 2002 were located inside the SPs and these firms' patenting activity. As Fig. 1 shows, three main 'waves' characterise the creation of the Finnish SPs,[2] The pioneer is Technopolis, born in 1982. It then takes three years to see other SPs being established. Overall, seven SPs are created during the first wave, which lasts until 1987. In 1989 a second and stronger wave begins. This lasts until 1992 and sees the establishment of the majority of the Finnish SPs. The third wave (1995–1999) constitutes a less intense momentum, during which time five SPs appear.[3] For 15 out of 21 (71.43%) SPs we gathered data about the Parks' tenants, three SPs declared not to host any company, whereas no information could be obtained about the remaining three Parks.

Table 2 shows some SP statistics relative to the year 2002. These regard: SPs' size, in terms of number of tenants; SP age, from the year each SP has been established until the 2002; and the presence of universities, outliers and incubators inside the Parks. By outliers we mean firms with more than 4,000 employees in Finland.[4]

The data regarding the SP tenants were collected as follows. We first listed all the firms and knowledge-based institutions that in the year 2002 were located inside the Finnish SPs (1,225 in total). Out of each firm we recorded the sector and degree of independence, i.e. whether or not it belonged to a holding/group. Further, we verified if the firm had several units/branches on the premises of one or more SPs, as well as the year in which each firm was established and the date it moved inside the SP. A questionnaire was then sent to the firms. It aimed to double check the data retrieved and to gather qualitative information, in particular to investigate the reasons why firms joined the Parks. The questionnaire did not include any innovation or patent

[2] By the 2006, three new SP had been created. More information about the Finnish SPs, their activities and the firms they host can be obtained from the Finnish Science Parks Association (www.tekel.fi).

[3] Additional data regarding the Science Parks, their location, year of creation and sectors covered are available from the author upon request.

[4] See Sect. 4.3 and the description of the variables used in the model, in particular big_j, for further details.

Table 2 Science Parks' size, age, and presence of universities, 'Big' firms and incubators[a]

	SP size (number of firms)	SP age[b] (born–end 2002)	Presence of	Uni	Big	Incub.
Mean	87	13.5	As % of	Overall number of SPs		
Std. dev.	53	3.9		79	71	71
Min	15	6		Overall number of firms		
Max	186	21		72	79	80

[a] Data regarding the 14 SPs where the firms in the sample are located

[b] Data in years

Table 3 Sample composition, firm size and firm age per sector

		Firm size (number of employees)						Firm age (number of years, born–end of 2002)					
Sector	As % of tot. number of firms	Mean	Std. Dev.	Skew	Kurt	Min	Max	Mean	Std. Dev.	Skew	Kurt	Min	Max
Soft&ICT	43	133.6	418.1	4	18.5	1	2200	6.6	5.6	1.7	6.6	1	31
Electronics	11	130.2	283	2.5	7.6	1	1000	13.8	8.1	0.5	3	1	33
Biotech	10	224.1	754.9	3.8	16.5	1	3400	9.2	7.2	1.4	4.5	1	28
Others	36	108.5	499.2	6.9	52.8	1	4000	12.5	8.8	0.9	2.9	1	33
Overall	100	133.6	479.7	5.5	36	1	4000	9.7	7.8	1.3	4	1	33

related question, to avoid that the respondents would self-select with respect to the variable of interest (i.e. firms' innovative output). The questionnaire reached 1,089 firm. A total of 345 (33%) of them answered.[5] From this first sample we pulled out those firms that said not to be located inside any SP,[6] and all the branches/units but one belonging to the same firm.[7] In addition, outliers were excluded and their presence in the SP accounted for through a dummy variable (see Sect. 4). Last, we took off the sample those firms born before 1970 (16 in total). We did so for the impossibility to fully track their innovative activity over time due to data constraints. The sample used in the present study is thus made of the remaining 252 firms, whose sector, size and age statistics are summarised in Table 3. The most represented sectors are: software and information and communication technologies (*soft&ICT*); electrics and electronics (*electr*); and biotechnology, medical devices and pharmaceuticals (*biotech*). *Others* constitutes a residual category where we group firms in industries like energy, pulp and paper, environment, food, construction, as well as consultancies of various types.

Next, we recorded the innovative activity of each firm, measured in terms of patents applied for at both the Finnish and the European level. Data were gathered from the National Board of Patents and Registration of Finland (Patentti- ja Rekisterihallitus, PRH) and the European Patent Office (EPO). As PRH's data cover the period 1970 onwards we restrict the analysis to the firms established in or after that very year, in order to avoid left truncation.[8]

Figure 2 pictures the patenting activity of the firms by sector and over time, i.e. both before and after joining the SPs. Table 4 offers some descriptive statistics regarding the years the firms spent inside (*yyin*) and outside (*yyout*) the SPs, as well as their patenting activity during their 'before' (*patout*) and 'after' (*patin*) period.

[5] Sheenan (2001) finds response rates to oscillate between 21.6% and 36%. Jobber and Saunders (1993) indicate that business-oriented studies' rate of response are sensitive to characteristics as e.g. length and number of questions.

[6] These firms (7) had been listed as tenants by the SPs themselves. Possibly their inclusion aimed to enhance the SP image, or was due to these firms having participated in some of the SP activities (as some firms said).

[7] We did so to avoid duplications. Overall, 14 cases were dealt with and quite easily. To this end, we considered elements as size (in number of employees), function and age of the various branches. In addition, information provided by the firms eased the decision.

[8] Left truncation would occur for the impossibility to track firms' innovative output before 1970.

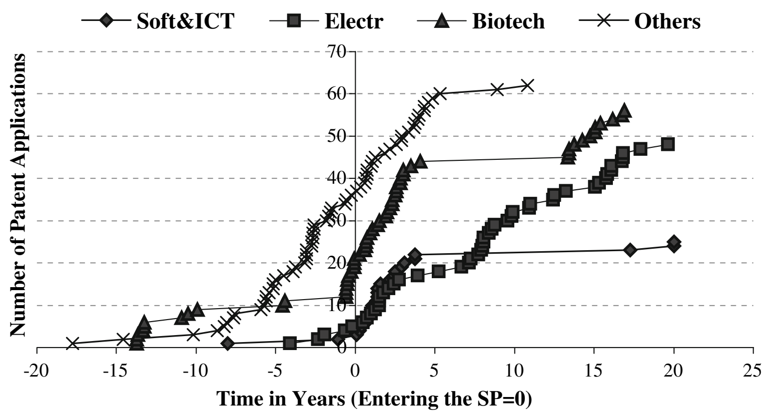

Fig. 2 Patent applications per sector and time

Table 4 Firm year and patent activity by period and sector

		yyout	yyin	patout	patin
Soft&ICT	μ	3.67	5.38	0.02	0.22
	σ	6.06	4.82	0.14	0.73
Electr	μ	6.61	7.65	0.21	1.79
	σ	9.39	6.23	0.83	4.64
Biotech	μ	10.08	6.13	0.84	1.40
	σ	9.50	4.53	2.25	3.28
Others	μ	5.18	5.64	0.38	0.28
	σ	9.66	4.25	1.42	1.05
Overall	μ	5.18	5.78	0.26	0.51
	σ	8.44	4.76	1.18	2.00

Only 19.92% of the firms in the sample patented at least once, whereas the vast majority of them (80.08%) shows no patenting activity during the period considered. Denoting by t_0 the time when the firms move inside the SPs, we also notice that firms patent more after acquiring the SP tenancy status: the 'after' period figure almost doubles the 'before' one (*patin* = 127; *patout* = 64).

4 The model

We look at the firms' before-VS-after innovative performance to see if the firms' patenting output of the 'after' period may in any way be related to their being located inside the SPs. To this end we look at the likelihood that a company i applies for patenting some invention k, both before and after locating inside the SPs. More precisely, we estimate the before-VS-after hazard rate of patenting, i.e. the probability that a company i would apply for a patent during the time interval considered, $[t,t + \Delta t]$, conditional on its survival (i.e. not having patented any invention) up to time t.[9] The analysis aims to investigate if and to what extent moving inside the SPs may exert any influence over the firms' innovative performance. We in fact suppose that locating inside the Parks should help firms innovating more, for two main reasons. Firstly, tenant firms may benefit from the services the SPs provide. Secondly, if we hold SPs to be institutions where knowledge is opportunely channelled, becoming a SP tenant should enhance the firms' innovative capacity.

4.1 Main features of the model

The duration model we estimate holds patenting as a repeated and event-dependent phenomenon and takes care of issues such as change of status, censoring and unobserved heterogeneity. We hold patents to be *repeated events* because a patent application will be filed each time a firm decides to rely on Intellectual Property Rights (IPR) to protect its innovative output. Besides, we consider patenting as an *event dependent* phenomenon, for three main reasons. Firstly, if the act of filing the first patent signals that the firm is innovation-oriented, it is reasonable to expect that the firm will continue to innovate and possibly seek again IPR protection. Hence, patenting for the first time may make further patents likely to occur. Our hypothesis is supported by Cefis (2003). She finds that first-patent

[9] Hazard rates represent a sort of transition intensity, their concept being akin to that of a conditional probability for tiny Δt.

threshold effects exist and that the probability to go from zero to one patent is much lower than the probability of patenting the *n*th invention, where $n \geq 1$. Secondly, we believe that 'dynamic economies of scale' (see the discussion of Geroski et al. 1997) might exist. At any point in time, increases in the volume of innovations produced by a firm make it more likely for the firm to continue innovating in the future. Learning mechanisms, also related to the patent filing procedure, may contribute to explain such a feature. Thirdly, and most fundamentally, we deem patents to be event-dependent phenomena as we hold knowledge to be cumulative. Firms carrying out innovative activities can exploit the knowledge accumulated and build on their portfolio to further innovate and patent. In such a case, we would observe a sort of individually generated and company-specific cumulative path of inventions, possibly also dependent upon the incoming spillovers.

"The issue of repeated events is one of dependence: second and subsequent events are likely to be influenced by, and therefore different from, first events" (Box-Steffensmeier and Zorn 2002, p. 1071). Holding patents to be repeated and event-dependent phenomena implies making the following hypothesis: the more the patents in portfolio, the more likely it is for a firm to patent again in the future. Econometrically, event-dependent phenomena violate the assumption, on which several models rely, that events occur independently. Dealing with repeated events as if they were independent would lead to implicitly impose, possibly mistakenly, that the influence of the covariates is the same across events. Besides, it could also lead to overstate the amount of information each observation provides and to incorrectly estimate standard errors. Would we not take event dependency into account, we would incorrectly estimate the firms' likelihood to patent over time and the role SPs might have played. Doing so, we would in fact attribute the same importance to both first and subsequent patents and thus over (under)-estimate the contribution of SPs to the innovativeness of their tenants.

Our duration model also pays attention to *unobserved heterogeneity* (or 'frailty', Lancaster 1990), as the firms in the sample might as well differ in characteristics that we do not explicitly control for. Unobserved heterogeneity might, for instance, be due to differences in the management ability of the firms, R&D expenditures, the education level of the workforce, the financial support some might have received by public agencies, etc. Although models with unobserved heterogeneity are computationally burdensome, frailty needs being taken care of to avoid inconsistent inferences (Van den Berg 2001).

In the analysis, we treat the event that firms move inside the SPs as a *change of status*. Although from a conceptual point of view events—in our case patenting—need being distinguished from a change of status, the latter does not pose major theoretical or empirical problems.

We hold that moving inside an SP is not determined by the main event we study, a firms' likelihood to patent, for two main reasons. On the one hand, the SP literature (e.g. Felsenstein 1994; Westhead and Storey 1994) suggests that Parks often prefer to secure rent income and to fill up their premises, rather than selecting prospect tenants. Besides, if and when selection happens, it is operated with respect to characteristics that are not related to the patenting activity of the firm (e.g. financial viability). In the case of Finland, the information we acquired support the hypothesis that SPs do behave as rent-seeking organizations. On the other hand, the qualitative data gathered through the questionnaire suggest that firms choose to locate inside the Parks simply because they find the SP premises particularly suitable, or for image/prestige reasons or to stay close to their suppliers/customers. We can thus reasonably rule out the existence of selection and self-selection problems determined by the variable of interest, i.e. the firms' patenting activity. Overall, the information obtained by both firms and Parks suggest that locating inside the SPs constitutes a fairly random process. Hence, we might be confident that the consistency of the estimates and the reliability of our results should not be undermined by endogeneity. Besides, endogeneity would become less of a concern if one considers that, even if the sample were composed of over-performers, firms should become comparatively more innovative once inside the Parks than they were in the 'before' period. This, of course, if Parks succeed to accomplish their innovation policy mission.

Finally, our *data* are *censored*, as the sample is made of firms that in the year 2002 were located inside the Finnish SPs, independently of the firms' age and length of their tenancy. Consequently, our observations are type I right censored (Klein and Moeschberger 1997), as we observe patenting events up to the 31st December 2002. We also have left censoring, as firms enter the study at different times, i.e. when they are established. However, both right and left censoring are easily dealt with, in both parametric and semiparametric models.

4.2 The econometric model

We analysed the time to the patenting event following the dominant approach of dealing with repeated events using variance-corrected Cox's proportional hazard models. Cox's (1972) partial likelihood method makes it possible to estimate the parameters β of a proportional hazard model without having to specify the baseline hazard. The strength of Cox's approach is that the effect of the covariates can be estimated very generally, given that the hazard is of the form $\lambda(t;\mathbf{x}) = \kappa(\mathbf{x})\lambda_0(t)$, where $\kappa(\cdot) > 0$ is a nonnegative function of $\mathbf{x}$ and $\lambda_0(t) > 0$ is the baseline hazard. However, the Cox model requires events to occur independently and, evidently, repeated and event-dependent processes violate this assumption. Besides, in presence of repeated events, the standard Cox model's estimates converge to a well-defined vector of the covariates' coefficients but the estimated covariance matrix is not appropriate for hypothesis testing (Lin and Wei 1989; Struthers and Kalbfleish 1984).[10] Hence, the need to use variance-corrected Cox's proportional hazard models, which basically estimate standard Cox models while adjusting the variance-covariance matrix in order to account for the individual-specific effects that may remain. Variance-corrected Cox's proportional hazard models address the potential for event interdependence and repeated events using robust variance estimates. Estimators are based on sandwich estimates and assume that observations are independent across units but not necessarily within units. Individuals might in fact face different event rates due to their own characteristics. In addition, in presence of multiple events, the occurrence of an event may condition (i.e. raise or lower) the probability that further events occur.

In the context of the Cox proportional hazard model:

$$h(t) = \lambda_0(t)\mathrm{e}^{(\mathbf{X_{it}\beta})}$$

$h(t)$ is the hazard of the event of interest, $\mathbf{X}_{it}$ is the vector of covariates and λ_0 is an unspecified nonnegative function of time (i.e. the baseline hazard). The robust variance estimator takes the form:

$$\mathbf{V_R} = \mathbf{V^{-1}BV^{-1}}$$

where $\mathbf{V^{-1}}$ is the usual variance estimate, i.e. the inverse of the information matrix $\mathbf{V}$, and $\mathbf{B}$ is a correction factor.[11]

The variance-corrected Cox's proportional hazard model used in the present study follows the conditional risk-set model proposed by Prentice, Williams and Peterson in 1981 (PWP). The model is estimated in inter-event or 'gap' time, i.e. the duration since the previous patent. In the PWP model the risk set for a patent event k at time t is represented by all the subjects that, at time t, have experienced the event $k-1$ but have not experienced event k yet. This implies that a firm cannot be at risk of patenting, e.g. for the third time unless it already has two patents in portfolio. Estimates are stratified by event rank (i.e. first patent, second patent, etc.). The baseline hazards are allowed to vary with the different event considered and robust standard errors are calculated. An interesting feature of the PWP model is that it accounts for the order of the events and thus provides efficiency gains over the model proposed by Wei, Lin and Weissfeld (1989).[12]

We follow the notation used by Kelly and Lim (2000), and denote by T_{ik} the 'true' total time of the kth patent event for the ith subject, and by C_{ik} the

[10] In alternative to variance corrected models, there are other models that allow for unit-specific effects. Such models may be broadly grouped under the name of 'fixed-effects' and 'random-effects' or 'frailty' models. In these groups repeated events are treated as a special case of heterogeneity at the unit level. See Box-Steffensmeier and Zorn (2002).

[11] The estimates of the variance-corrected standard errors are typically larger than those obtained from estimates based on $\mathbf{V^{-1}}$. This is due to the fact that unobserved intracase correlations are generally positive. See Box-Steffensmeier and Zorn (2002) for the calculation of the standard error.

[12] They treat repeated events as competing risks and let each observation being at risk for the kth event from the beginning of the period under study.

censoring time for the kth patent event in the ith subject. X_{ik} is the corresponding observed duration, with $X_{ik} = \min\ (T_{ik}, C_{ik})$ The censoring indicator is $\delta_{ik} = I(T_{ik} \leq C_{ik})$, where $I(\cdot)$ is the indicator variable. $I(E) = 1$ if E is true and $I(E) = 0$ otherwise.

Inter-event times are defined as $G_{ik} = X_{ik} - X_{i,k-1}$ with $X_{i0} = 0$, that is the time when the firm enters the study, i.e. when it established.

The hazard function for the kth patent for the ith subject at time t is $\lambda_{ik}(t)$, with

$$\lambda_{ik}(t; \mathbf{Z}_{ik}) = \lambda_{0k}(t - t_{k-1})e^{\boldsymbol{\beta}' Z_{ik}(t)}$$

where $Z_{ik} = (Z1_{ik},\ldots,Z_{pik})'$ is the covariate vector for the ith subject with respect to the k th patent, and K is the maximum number of patents within a subject. $\lambda_0(t)$ denotes a common baseline hazard for all patent events and $\lambda_{0k}(t)$ is the event specific baseline hazard for the kth patent. Finally, $\boldsymbol{\beta} = (\beta_1,\ldots,\beta p)'$ is the $p\times 1$ vector of regression parameters to be estimated.

The partial likelihood L is defined as:

$$L(\beta) = \prod_{j=1}^{d} \frac{\lambda(t_{(j)})}{\sum_{k \in R(t_{(j)})} \lambda(t_{(k)})}$$

where d is the observed number of patenting events.

Let the ordered event times be $t_{(1)} < t_{(2)} < \ldots < t_{(\mathrm{d})}$, where $t_{(j)}$ is the jth ordered event time, and $R(t_{(i)})$ the set of individuals at risk at time $t_{(i)}$. Our PWP model's partial likelihood function, in inter-event time, is given by:

$$L(\beta) = \prod_{i=1}^{n} \prod_{k=1}^{K} \left(\frac{e^{\beta' Z_{ik}(X_{ik})}}{\sum_{j=1}^{n} Y_{jk}(X_{ik}) e^{\beta' Z_{jk}(X_{ik})}} \right)^{\delta_{ik}}$$

where $Y_{ik}(t) = I(G_{ik} > t)$ and $Z_{jk}(X_{ik})$ is replaced by $Z_{ik}(X_{i,k-1} + G_{ik})$.

We empirically model the time to patent using a continuous-time framework, as data are recorded on a daily basis.

4.3 Variables and hypotheses

A set of both time-varying and fixed covariates accounts for the firms' and Parks' characteristics. $Onoff_{it}$ is a dummy variable denoting whether the ith firm is located inside ($onoff = 1$) or outside ($onoff = 0$) of the SP at time t. We would expect the $onoff_{it}$ coefficient to be significant and positive if SPs succeed in constituting seedbeds of innovation.

The other time-varying covariates we use are: Age_{it}, $Portfolio_{it}$, $TinSP_{it}$ and $SPold_{lt}$.

Age_{it} reflects the age of the company i at time t. We assume firms to be established on the 1st of January of the corresponding year, unless otherwise expressly specified by the firm. Firms start being 'at risk' on the date they have been established. Holding knowledge to be cumulative would lead to expect a significant and positive age_{it} coefficient. However, if diminishing returns to R&D exist (see Klette and Griliches 2000, in this respect) age_{it} could exhibit a negative coefficient: the older the firm, the slower the pace at which it would generate new innovations.

$Portfolio_{it}$ is a non-negative variable reflecting the number of patents each applicant has in portfolio at time t_k, i.e. when applying for the kth patent.[13] If, as we suppose, innovative activities are persistent (Cefis 2003), $portfolio_{it}$ should exhibit a both significant and positive coefficient. Our hypothesis is that the more an applicant has patented in the past, the more likely it is that it patents again in the future.[14]

$TinSP_{it}$ is a non-negative continuous covariate reflecting the time that firm i has spent inside the SP. $TinSP_{it}$ takes value zero when the $onoff_{it}$ state variable is zero, thus implying that, at time t, firm i has not moved inside the SP yet. We assume firms to move inside the Parks at the beginning of the considered year, unless otherwise expressly declared by the interviewed. We would expect $tinSP_{it}$'s coefficient to be significant and positive if firms profit from being SP tenants.

$SPold_{lt}$ reflects the age, at time t, of Park l where firm i is located. We use it as a proxy for the Parks' learning ability and as an indicator of how established Parks' networks are. If we hold knowledge to be cumulative, ceteris paribus we should expect $spold_{lt}$ to show a significant and positive coefficient.

The time-invariant regressors used in the model are: $size_i$, $group_i$, $soft\&ICT_i$, $electr_i$ and $biotech_i$, which are firm-related variables, and $SPsize_l$, big_l, and uni_l accounting for Park-specific characteristics.

[13] Obviously, for those companies that never applied for a patent $Portfolio_{it}$ is always zero.

[14] However, this does not imply that firms should patent more often.

$Size_i$ reflects the number of employees the firm had in Finland in the year 2002. We follow Acs and Audretsch (1988) and consider the size of the entire firm and not only of the on-Park subsidiary/unit. Ceteris paribus, we expect $size_i$ to be significant and positive. Our hypothesis relies on, among others, Scherer (1980, 1984), Pavitt et al. (1987) and Acs and Audtretsch (1990, 1991). Scherer (1980, 1984) finds patents to rise—although less than proportionally—with firm size. Pavitt et al. (1987) find the number of innovations per employee to be above average in both firms with less than 1,000 and more than 10,000 employees. Acs and Audtretsch (1990, 1991) see that small firms generate more innovation per thousand employees than large companies. Although aware that the number of employees is likely to change periodically, we use the year 2002 data only, as we could not to track firms' size over time. Our modelling choice could bias the estimates if we presuppose the existence of a systematic measurement error, linked to the way in which companies grow. This would be the case if, as Jovanovic (1982), Evans (1987) and Hall (1987), we would argue that better performers—i.e. more innovative firms—grow, and possibly grow faster. In any case, it is not clear that firms would grow only or principally as a consequence of their patenting activity. If the different patterns happen randomly our estimates should not be off the mark.

$Group_i$ is a time-invariant dummy regressor denoting whether the ith company belongs to a holding/group or not. We follow Geroski et al. (1997), who find that being independent has a strong positive effect on the innovation spell length. We expect that being part of a group would diminish the firms' likelihood to patent. Our explanation is linked to the possible existence of corporate patenting rules. On the one hand, patents may be assigned to the mother company or to other affiliates to serve corporate interests and/or to avoid ex post licensing problems. On the other hand, different affiliates of the same group may exist and patent under different names, thus jeopardising the researcher's ability to track the overall innovative output of the firm.

$Soft\&ICT_i$, $electr_i$ and $biotech_i$ are fixed covariates that account for the most represented sectors in the sample. We control for the possible industry-specific effects that might exist as they can be even more important than firm size in shaping firms' R&D intensity (Cohen et al. 1987) and likelihood to patent.

Finally, a troika of time-invariant regressors attempts to capture the possible spillover effects generated within the SPs: $SPsize_l$, big_l, and uni_l.

$SPsize_l$ is a count variable and reflects the overall number of tenants located inside the lth SP in the 2002. $SPsize_l$ figure may differ from the number of companies SPs hosted over time, but no further data were available in this respect. In any case, three arguments lead us to believe that the value of $SPsize_l$ should not be volatile over time. Firstly, being rent-seeking organization, SPs will always try to rent all available premises. Secondly, firms are not likely to change their location too often, as moving is costly. Thirdly, SP premises' supply is likely to be inelastic, as infrastructures can only be built or modified over the long term. We expect $SPsize_l$'s coefficient to be significant and positive, as we suppose that the higher the number of firms in the Park the bigger the probability that spillovers occur.

Big_l is a dummy covariate that highlights the presence of outlying companies inside the SP. These outliers, i.e. firms having more than 4,000 employees in Finland in the year 2002, were pulled out of the sample and their presence is accounted through big_l. The reason why we do so is two-fold. On the one hand, outliers are extremely 'prolific', patenting-wise, and their innovative performance would 'dwarf' the other tenants' innovative activity. Besides, as Nokia, Sonera and Orion (to name but a few of them) are somehow 'ubiquitous', it would be extremely hard to understand if their patenting is—at all—influenced by their being located also inside the SPs. On the other hand, we need to account for the outliers' presence inside the SPs as these companies might positively influence the other firms' innovativeness. Information may spill over and know-how be transmitted when outliers interact with the other SP tenants. Our hypothesis is backed by Acs and Audretsch (1988) who find that small firms belonging to sectors prevalently made up of large firms are more competitive and generate proportionally more innovations.[15]

[15] The authors also hold the total number of innovations to be positively related to the extent to which an industry is made up of large firms. Given the country and the sectors we take into account, similar dynamics can apply to the Finnish SPs' case.

Uni_l is a dummy covariate used to capture possible within-the-Park spillover effects. It takes value one if there is at least one university technical department/laboratory or research centre located inside the SP. We follow Löfsten and Lindelöf (2002) and expect that SP tenants should be able to establish a comparative higher number of links with universities and research centres than outside-the-Park firms. These links should emerge through a significant uni_l coefficient. Further, we expect uni_l's coefficient to be negative. Our hypothesis is supported by Hall et al. (2003) who find that projects with universities may experience relatively more difficulties and delays, even if they are less likely to be aborted prematurely. This fact, paired with right censoring, might lead to observe a significant and negative uni_l coefficient. In any case, our hypothesis is not at odds with the general belief (among others, Zucker et al. 1998; Westhead 1997) that being close to basic science institutions is good for companies.[16] We think that positive effects should—solely or principally—be observable in the long term, whereas our duration model would make immediately visible the delays that such relationships might determine on the firms' patenting activity.

Finally, the regressor $incub_l$ accounts for the presence of incubators inside the SPs. Incubators are institutions that provide early-stage businesses with hands-on support and services, such as marketing, business and legal support, finance raising, mentoring, and so on. Ex ante, arguments exist to expect either a positive or a negative coefficient. On the one hand, $incub_l$'s coefficient might be negative, due to the type of companies incubators normally host. Early stage firms are, basically, 'market rookies' that might need time to get settled and become active, also patenting-wise. On the other hand, the help they receive when incubated should make young firms perform well innovation-wise, i.e. $incub_l$'s coefficient should be significant and positive. This last hypothesis is somehow backed by Massey et al's (1992) findings about incubators being moderately successful in constituting seedbed areas for new firms.

[16] Strengthening the links with universities and research centres should improve firms' access to well-trained human resources and scientific knowledge.

5 Estimating the firms' likelihood to patent

Our empirical analysis aims to assess if, how and how much locating inside the SPs affects firms' likelihood to patent, and to investigate the role played by the SPs' main features. We begin by estimating a model that includes only the firm-related regressors plus $onoff_{it}$ as control variables ('Model 8'). We then progressively introduce the SP-related covariates. These enter the model linearly and are previously multiplied by $onoff_{it}$. We do so because our aim is to assess the 'before' VS 'after-joining-the-SP' performance of the firms, and not to estimate the firms' likelihood to join SPs on the basis of Parks' characteristics.

Overall, seven variance-corrected Cox models are estimated, 'Model 8' to 'Model 14', characterised by a progressively bigger number of variables (i.e. 8–14 regressors). These stepwise estimations are run twice, both allowing the number of observations to vary and holding it constant, i.e. dropping missing values. Doing so, we aim to check if and how much the composition of the sample affects the estimates. Specification tests are run over the 14-variable PWP model. We first check the proportional hazards assumption using a test based on the generalisation by Grambsch and Therneau of the scaled Schoenfeld residuals on functions of time (Cleves et al. 2002; Therneau and Grambsch 2000). We then use the martingale residuals (Borgan and Langholz 2005; Sasieni and Winnet 2003) to determine the functional form of the covariates to be included in the model. Finally, we assess the overall model fit through the Cox-Snell residuals. All the tests suggest that the model is adequately parameterised and that $\mathbf{X_{it}}\boldsymbol{\beta}$ is well specified.

We also estimate some parametric models, to be more confident that the Cox model represents the correct choice. The Cox model in fact assumes the covariates to multiplicatively shift the baseline hazard function and leaves $\lambda_0(t)$ unestimated. This implies that no assumptions are made about the shape of the hazard over time and that the baseline hazard is given no particular parameterisation. Conversely, parametric models exploit the information contained in the data in a different way[17] and parameterise the baseline hazard $\lambda_0(t)$.

[17] Semiparametric methods make comparisons between subjects at the times when failures occur, whereas parametric models use probabilities reflecting what has occurred over the whole interval considered (using what is known about the subject during that interval).

We, therefore, estimate variance-corrected PWP Exponential, Weibull and Gompertz parametric models, as we lack of a priori good reasons to believe that the hazard would follow a certain shape. The estimates reveal that only the Exponential and Weibull models are possible candidates to adequately parameterise the baseline hazard, whereas the Gompertz is ruled out due to its positive log-likelihood value. Of the two remaining parametric models, the Weibull exhibits the largest log-likelihood, whereas the Exponential performs better according to the Akaike Informative Criterion (AIC). We also perform some (graphic) tests and inspections[18] to further investigate the performance of the parametrised models. These show that the baseline hazard is initially increasing, although not more than linearly, and that after a certain point it has no clear shape.[19] Overall, the tests carried out suggest the use of the variance-corrected Cox proportional hazards model, as its flexible parameterisation of the $\lambda_0(t)$ avoids imposing restrictions on the shape of the hazard rate. This choice is further backed by our interest to estimate hazard ratios rather than to predict the time-to-failure.[20]

5.1 Results

Table 5 shows the results of the Cox's estimates of Model 8 to Model 14 with the number of observations held constant.[21] The exponentiated coefficients we show in Table 5 and the other tables should be interpreted as the ratio of the hazards for one-unit change in the corresponding covariate. In general, continuous variables should exhibit very small coefficients, as they account for the effect of an additional unit of the regressor over the dependent variable. Dummy variables should instead be characterised by bigger coefficients, as they reflect a yes-or-no type of answer. We show z-statistics rather than standard errors, as the latter would not help the readability of the estimates. When fitting the models in the exponentiated coefficients scale, the reported standard errors would in fact be those obtained by applying the delta method to the original standard error estimates. Conversely, z-statistics are easy to read, have been calculated using the original coefficients and have the usual interpretation. Last, for simplicity variables are not indexed, but simply written in italic font.

5.1.1 Firms' and Parks' characteristics

We first analyse the way firm- and SP-related variables affect patenting and then comment on the behaviour of the *onoff* regressor.

As for the firm characteristics, *size*, *age* and *portfolio* seem to always play a role in shaping firms' likelihood to patent, independent of the firms being inside or outside the SPs. Each additional employee has a very small although positive effect over firms' likelihood to patent (0.0627–0.1004%). Conversely, the coefficients related to the age of the firm suggest that the older the firm, the less likely to patent it is. For each additional year of age the average firm has a 24.76–31.86% lower likelihood to patent. Last, the variable related to the patent portfolio of firm i at time t exhibits a significant and positive coefficient. Increasing by one unit the number of patents a firm already has at time t leads to 10.45–20.42% higher likelihood to patent. Such results support our hypothesis of patenting as a repeated and event-dependent phenomenon.

The estimates do not shed light on the effect that belonging to a group might have on the innovative performance of the firms in the sample, as *group* is never significant. Likewise, the variables accounting for the specific industry the companies belong to are almost never significant either. *Electr* is the sole sector dummy showing a significant coefficient, but only in Models 8 and 9. As soon as we introduce the SP-related variables, *electr* stop being significant and its coefficient becomes smaller and then turns negative. In general, the behaviour of the firm and Park variables suggests that matching issues may be at

[18] For instance, we fit a model in which we directly include t, through constructing time-varying covariates for t considering an equal number of observations in each time group/step. See Cleves et al. (2002) in this respect.

[19] The Gompertz model would not be appropriate, as its parameterisation does not allow the hazard to increase at a decreasing rate, but only to increase or decrease exponentially.

[20] The parametric estimates are available upon request from the author.

[21] In Appendix, Table 1A shows the same estimates carried out while allowing the number of observations to vary, plus the 'Model 15' and 'Model 16' estimates. See Sect. 6.3 for more details.

Table 5 Variance-corrected PWP Cox Models 8–14 (Constant # Obs.; Time in Days)

Variables	Model 8 Haz Rat (z)	Model 9 Haz Rat (z)	Model 10 Haz Rat (z)	Model 11 Haz Rat (z)	Model 12 Haz Rat (z)	Model 13 Haz Rat (z)	Model 14 Haz Rat (z)
Onoff	.1457** (−4.54)	.1354** (−4.48)	1.0797 (0.14)	2.0777 (1.02)	1.2306 (0.32)	.8075 (−0.31)	.9442 (−0.07)
Tenants' characteristics							
Size	1.0006** (2.41)	1.0006** (2.45)	1.0010** (3.02)	1.0010** (3.16)	1.0009** (2.79)	1.0009** (2.73)	1.0009** (2.74)
Group	.8780 (−0.39)	.8599 (−0.41)	.7993 (−0.69)	.8259 (−0.57)	.8711 (−0.38)	.7598 (−0.81)	.7477 (−0.85)
Age	.9992** (−3.62)	.9992** (−5.33)	.9990** (−6.54)	.9990** (−6.27)	.9989** (−6.72)	.9990** (−6.06)	.9990** (−6.08)
Portfolio	1.1091** (3.33)	1.1046** (2.67)	1.1963** (4.58)	1.2042** (4.67)	1.1919** (5.27)	1.1725** (4.62)	1.1740** (4.52)
Softwareict	.8540 (−0.39)	.8299 (−0.46)	1.4449 (0.88)	1.5772 (1.13)	1.0734 (0.17)	1.1685 (0.34)	1.1804 (0.35)
Electr	4.1167** (3.95)	3.8647** (2.98)	1.6788 (0.86)	1.9066 (0.99)	.9914 (−0.01)	.5522 (−0.78)	.5325 (−0.87)
Biotech	1.2966 (0.29)	1.2735 (0.29)	1.1283 (0.18)	1.1266 (0.17)	.5687 (−0.87)	.6611 (−0.74)	.6631 (−0.74)
SP-related features							
TinSP		1.0000 (0.25)	1.0003 (1.52)	1.0003 (1.38)	1.0003 (1.47)	1.0004* (1.84)	1.0004* (1.74)
SPold			.9995** (−3.24)	.9994** (−3.16)	.9994** (−3.16)	.9992** (−3.56)	.9992** (−3.43)
Uni				.4720 (−1.21)	.2705** (−2.04)	.1240** (−3.77)	.1071** (−3.09)
Big					5.3887** (3.95)	7.5298** (4.21)	7.6507** (4.26)
SPsize						1.0129** (3.00)	1.0144** (2.58)
Incub.							.7697 (−0.28)

Number of obs.	Model	log pseudo-likelihood	Wald chi2	Prob > chi2
273	8	−329.47631	127.12	0.0000
	9	−329.3413	163.96	0.0000
	10	−305.7889	183.01	0.0000
	11	−303.65429	186.39	0.0000
	12	−296.9628	160.51	0.0000
	13	−288.29715	156.79	0.0000
	14	−288.22064	156.83	0.0000

Breslow method for ties. Standard errors adjusted for clustering on companies

** = significant at 5% level, * = significant at 10% level, z values in parentheses

stake. We will get back to this point later whereas here we focus on the behaviour of the SP-related regressors.

Three of them, namely *SPold*, *big* and *SPsize*, are always significant. Their coefficients exhibit progressively bigger values, the higher the number of variables included in the model. Other things being equal, the age of the SP at time *t* affects negatively the likelihood to patent of the tenants. For each additional year of age, Park *l* might contribute to make firms 17.82–24.54% less likely to patent. This result may suggest that SPs do not learn over time nor do they establish better links and networks. It also indirectly argues in favour of our claim about the absence or negligibility of selection and self-selection mechanisms.

The presence on Park of big companies instead proves to very positively affect the tenants' likelihood to patent, by a factor varying between 4.39 and 6.65. Likewise, the more the firms in the Park, the better the tenants' innovative performance: each additional tenant makes firms on average 12.94–14.38% more likely to patent. Finally, the estimates confirm our expectations about the negative effect that the presence of technical universities and research centres might have on the tenants' likelihood to patent (−72.95 to −89.29%).

Overall, the behaviour of *big*, *uni* and *SPsize* supports the hypothesis that spillovers mechanisms do take place inside the SPs. On the one hand, proximity, i.e. the co-location within the SP, makes firms able to profit from the knowledge spillovers generated by the outliers.[22] On the other hand, if SP

[22] In general, we are inclined to think that knowledge would spill out of outliers to be absorbed by smaller tenants, rather than the contrary. We do not exclude that information might

firms enjoy a higher probability of engaging in R&D activities with Universities (as found by Löfsten and Lindelöf 2002), such links might have a negative effect on the tenants' likelihood to patent.[23]

Last, the estimates do not offer any insight about the role of incubators. We will come back to this issue later to try and disentangle the effect that *incub* might have on the 'very-young-when-entering-the SP' firms from the one it might have on the average tenant.

5.1.2 Locating inside the SP: does it matter?

We here focus on the behaviour of *onoff* in conjunction with the pattern shown by *tinSP* and the other SP related variables. On the one hand, 'Model 8' and 'Model 9' seem to point out that locating inside a SP might be detrimental to the average firm's innovative output, as it lowers tenants' likelihood to patent (−85.43 to −86.56%). On the other hand, *onoff* coefficient's values, although not significant, change dramatically once we include the SP related variables. Besides, *tinSP*'s coefficient is always positive and becomes significant in the last two specifications. Models 13 and 14 in fact show that per each additional year spent inside the SPs firms increase their likelihood to patent by 13.80–13.95%. The conflicting evidence offered by *onoff* and *tinSP* can be possibly solved by looking at *onoff* coefficient's value and sign vis-à-vis the behaviour of the other SP-related variables' coefficients. We in fact observe that introducing the SP-related variables, particularly *SPold*, affects the behaviour of both *onoff* and *tinSP*. In order to test the hypothesis that *onoff* and *tinSP* might capture the negative effect of *SPold*, we re-estimate the model without including *tinSP* and see that *onoff*'s coefficient becomes positive, although still not significant.

Overall, results seem to suggest that it is not locating inside the SPs as such that affects firms' likelihood to innovate. What matters is being a firm with certain characteristics that locates in a Park exhibiting some specific features.

6 Robustness checks

In search for further evidence we investigate the effect that some SPs' characteristics might have on the patenting likelihood of the tenants. To this end four more variables are used, each supposed to tackle a specific issue.

6.1 Role of universities

The estimates shown point out that, if anything, the presence in the SP of academic departments and research centres affects negatively the innovative performance of the tenants. However, we tend to believe that, in the long run, such result should be reversed. We suppose that interacting with universities for a longer time should make tenants able to ultimately profit from it. If universities concentrate more on fundamental science they might need relatively more time to make their inventions become commercially viable, i.e. patentable innovations. In order to test such a hypothesis we build *TinSPuni* = *tinSP*uni* thus investigating whether spending more time inside a with-university SP affects positively the patenting performance of the tenants (see 'Model 15' in Table 6).

6.2 Role of incubators

The non significance of the *incub*'s coefficient might have been due to the absence of variables controlling for both the event of actually having been incubated and for the incubation time-length. However, as we lack of such data, we try to indirectly verify the effect that (possibly) being incubated might have on firms. To this end we build a variable called *young* = *(tinSP/age)*incub* and include it in a new specification called Model 16 (Table 6). *TinSP/age* is a ratio obtained by dividing the time that the *i*th firm has spent inside the SP by its own age, at time *t*. It tells the lifetime proportion that firm *i* has spent inside the SP. The closer to one the value of the ratio, the younger the firm at time *t*, the higher the

Footnote 22 continued
also flow in the opposite direction, but we think that outliers absorb outside knowledge in a different way, e.g. by buying particularly innovative small companies.

[23] See also Dechenaux et al. (2005) and Thursby et al. (2001) about firms cooperating with HEIs.

Table 6 Cox proportional hazard model variance-corrected estimates: Models 14–18, SPcycle and Spwave (Constant number of Obs.; Time in Days)

Variables	Model 14 Haz Rat (z)	Model 15 Haz Rat (z)	Model 16 Haz Rat (z)	Model 17 Haz Rat (z)	Model 18 Haz Rat (z)	SPwave Haz Rat (z)	SPcycle Haz Rat (z)
Onoff	.9442 (−0.07)	5.6472* (1.90)	27.5448** (2.88)	24.8709** (2.04)	90.9286** (3.59)	8.2508 (1.54)	8.1232 (1.42)
Tenants' characteristics							
Size	1.0009** (2.74)	1.0009** (2.51)	1.0010** (2.40)	1.0012** (2.59)	1.0014** (2.71)	1.0007 (1.22)	1.0007 (1.20)
Group	.7477 (−0.85)	.7009 (−0.96)	.5743 (−1.23)	.3820* (−1.90)	.3740* (−1.85)	.9007 (−0.18)	.9782 (−0.04)
Age	.9990** (−6.08)	.9990** (−6.17)	.9989** (−6.45)	.9987** (−6.44)	.9985** (−7.19)	.9982** (−7.71)	.9983** (−8.14)
Portfolio	1.1740** (4.52)	1.1562** (3.88)	1.1971** (4.19)	1.1126** (2.57)	1.0994** (2.69)	1.1419** (3.54)	1.1403** (3.74)
Softwareict	1.1804 (0.35)	1.2594 (0.49)	1.1788 (0.29)	1.5789 (0.73)	2.8738 (1.48)	2.0273 (0.94)	1.9598 (0.90)
Electr	.5325 (−0.87)	.6036 (−0.72)	.3214 (−1.55)	.0066* (−1.93)	.0117** (−2.57)	.0072** (−3.38)	.0113** (−3.15)
Biotech	.6631 (−0.74)	.6363 (−0.76)	.7791 (−0.44)	.6275 (−0.86)	.1121** (−2.04)	.0216** (−2.91)	.0311** (−2.82)
SP-related features							
TinSP	1.0004* (1.74)	.9988** (−2.93)	.9977** (−3.50)	.9985* (−1.79)	.9980** (−3.00)	.9973** (−3.75)	.9972** (−3.92)
SPold	.9992** (−3.43)	.9992** (−3.42)	.9994** (−2.87)	.9988** (−3.81)	.9988** (−4.49)	.9989** (−4.27)	.9992** (−2.65)
Uni	.1071** (−3.09)	.0154** (−5.85)	.01471** (−4.01)	.0363** (−2.32)	.0089** (−3.94)	.0025** (−4.36)	.0024** (−4.58)
Big	7.6507** (4.26)	7.4224** (4.29)	4.5841** (2.43)	10.4739** (2.92)	17.1307** (2.72)	39.8663** (2.96)	33.3140** (3.12)
SPsize	1.0144** (2.58)	1.0141** (2.56)	1.0174** (3.03)	1.0254** (2.73)	1.0225** (2.36)	1.0310** (3.61)	1.0299** (3.62)
Incub	.7697 (−0.28)	.8257 (−0.22)	.0149** (−2.72)	.0190** (−3.00)	.0329** (−2.88)	.1975 (−1.09)	.1914 (−1.22)
Interactions							
SPuni		1.0016** (3.52)	1.0022** (3.22)	1.0015 (1.58)	1.0017** (2.66)	1.0024** (3.41)	1.0025** (3.56)
Young			64.5949** (3.41)	59.9302** (2.82)	13.6646** (2.67)	17.1297** (2.97)	15.9562** (3.14)
SPoldelectr				1.0008* (1.93)	1.0010** (3.36)	1.0009** (3.69)	1.0009** (3.69)
Bigbiotech					1.0009** (4.17)	1.0012** (4.89)	1.0011** (4.63)
Spwave2						4.3324** (2.64)	3.7618** (2.43)
Spwave3						87.1808** (2.91)	83.5713** (3.17)
Spearly							5.3051 (1.16)
Spdevelop							2.2929 (0.99)

Table 6 continued

Variables	Model 14 Haz Rat (z)	Model 15 Haz Rat (z)	Model 16 Haz Rat (z)	Model 17 Haz Rat (z)	Model 18 Haz Rat (z)	SPwave Haz Rat (z)	SPcycle Haz Rat (z)
Spmature							2.6071* (1.86)

Number of obs.	Model	log pseudo- likelihood	Wald chi2	Prob > chi2
273	14	−288.22064	156.83	0.0000
	15	−280.72441	154.72	0.0000
	16	−262.58883	373.64	0.0000
	17	−256.21249	298.61	0.0000
	18	−241.29833	309.81	0.0000
	SPwave	−232.36027	389.32	0.0000
	SPcycle	−230.52749	367.14	0.0000

Breslow method for ties. Standard errors adjusted for clustering on companies

** = significant at 5% level, * = significant at 10% level, z values in parentheses

possibility that it got incubated. We would expect *young* to be significant and its coefficient to be positive if incubators succeed in nurturing young firms.

6.3 Matching: uncovering interactions

Saying that matching issues might be at stake implies holding that the patenting performance of the tenants might be affected by particular combinations of both firm and Park characteristics. We here investigate the possible existence of some of them, as the size of our sample does not allow to include in the model all the many interaction terms that can be constructed.

In particular, we focus on two interactions. The first one regards the relationship possibly existing between the age of the SP and being an *electr* firm. The estimates highlight that introducing *SPold* makes *electr*'s coefficient turn not significant. Besides, the step-wise introduction of the Park-related variables makes *electr*'s originally positive coefficient become first smaller and then negative. We thus investigate whether *electr* firms benefit from locating inside the oldest Finnish SPs. To this end we create *SPoldelectr* = *SPold**electr*. Our intuition being correct, SP*oldelectr*'s coefficient should both be significant and positive.

The second interaction we check concerns the possible links existing between being a firm in the *biotech* sector and locating in an SP where outliers are present. We do so as we notice that *biotech*'s coefficient, although never significant, remains positive until the moment we introduce *big* and then turns negative and remains so throughout the estimates. The interaction term we construct takes into account the time factor, i.e. how long the *i*th *biotech* firm has been inside the SP: *bigbiotech* = *big**biotech**tinSP*. We do so aware that innovating may take comparatively longer time in the *biotech* industries. We expect *bigbiotech* to be significant and positive if *biotech* firms benefit from locating and remaining for some time inside SPs where also *big* companies are located.

6.4 Estimates' results

Table 6 shows the PWP Cox variance-corrected estimates of Models 14, plus Models 15–18, i.e. the ones obtained by gradually introducing the interaction terms. It also shows the 'SPwave' and 'SPcycle' models, to be dealt with in the next section.

The estimates of Models 15–18 basically confirm the role played by characteristics as firm size, firm age and number of patents in portfolio at time *t*, as well as SP age, number of tenants and the presence in the Park of both outlying companies and universities. Although differences can be sometimes noticed in the values of the exponentiated coefficients, these differences never force us to revise the interpretation of the underlying phenomenon.

Conversely, two interesting changes can be observed with respect to *tinSP* and *onoff*. On the one hand, introducing the interaction variables, in particular *TinSPuni*, makes *tinSP*'s coefficient turn negative and remain constantly so throughout the estimates. On the other hand, *onoff*'s coefficient changes dramatically in significance, sign and magnitude: it becomes significant and positive in Model 15 and its values climb up the more the variables in the model. Unfortunately, we cannot offer any plausible explanation of why *onoff*'s coefficient increases so much. Still we are inclined to interpret our latest results as follows: once specific interactions are uncovered, locating inside the SPs might, ceteris paribus, enhance the tenants' likelihood to patent. This seems to be true the longer the tenants stay inside the SPs and if and when universities are around. If on average the presence of universities dramatically lowers SP tenants' likelihood to patent, when controlling for both firms' and SPs' characteristics we see that the marginal contribution of an additional year spent inside a 'with-uni-Park' varies between 81% and almost 2.5 times more. Hence, the presence of Universities can contribute to increase the likelihood to patent of those firms able to enjoy university proximity for a 'long enough' time. As for the other interaction terms, the estimates confirm the negative effect that incubators might have on the average tenant's patenting activity. Conversely, incubators seem to be able to dramatically increase (13–63 times more) the likelihood to patent of those firms joining the Parks when very young.

Last, the sector-related interaction variables. The positive trend initially captured by *electr* disappears. The estimates suggest that, on average, belonging to the electronics sector could almost halve the tenants' likelihood to patent, unless the SP where the *electr* firm is located is 'aged'. *Electr* tenants perform 32.18–43.08% better per each-year older the Park is. Learning processes might help explaining such results. As for the companies in the *biotech* sector, the estimates only vaguely suggest a comparatively lower likelihood to patent of the firms in the *biotech* sector. *Biotech*'s coefficient, which is always negative but never significant, becomes significant only in Model 18. This feature and the behaviour of *bigbiotech* seem to suggest that the likelihood to innovate of *biotech* firms may improve the longer they locate inside SPs where outliers are present.

Overall, robustness checks clearly point out the existence of interactions between some of the firms own characteristics and the Parks' main features.

6.5 Parks: first movers' disadvantage and learning

Finally, we investigate some Park-related issues. We here focus on two of them in particular: if first movers' disadvantages exist; and if SPs are able to learn, through time, how to better support their tenants.[24] We do so as the estimates carried out so far suggest that the Park age negatively affects the likelihood to patent of the tenants. Possibly, the ability of younger SPs to more effectively accomplish their innovation supporting mission is due to the younger SPs' ability to avoid the mistakes made by the pioneers. If such first mover disadvantages (Rauch 1993) exist, we should empirically observe that those Parks established during the second and the third waves perform better than their predecessors. To this end, we construct the 'SPwave' model, whose specification includes two additional dummies. *Spwave2* accounts for the *l*th Park being born during the second wave, and *spwave3* reflects that the SP has been established during the third wave. The control group is represented by the pioneer SPs, i.e. those created during the period 1982–1987. Our hypothesis being correct, we should observe significant and positive coefficients for *SPwave2* and *SPwave3*.

We also verify if SPs are able to learn through time and improve their effectiveness. To this end we generate three dummies that reflect the *l*th Park's life cycle at the time when the *i*th tenant applies for its *k*th patent application. *SPearly* takes value 1 if the Park where the *i*th tenant is located is up to 5 year old at the time of the *k*th event; *SPdevelop* takes value 1 if the SP is between 5 and 10 year old; whereas *SPmature* points out the Park being between 10 and

[24] We also investigated the effect that being a 'specialised' SP might have on the tenants' likelihood to patent. To this end, we subdivided SPs into subgroups, according to the number of sectors they specialise in. No evidence emerged in favour or against the specialisation/diversification hypothesis.

15 year old at the time of the considered patent. The control group is represented by the Park being aged more than 15 years at the time of the *k*th patenting event. Supposing that Parks could learn through time would imply expecting *SPearly*, *SPdevelop* and *SPmature*'s coefficients to be significant and positive. Furthermore, as time is needed to make up for the mistakes made and to accumulate knowledge, we could reasonably expect progressively bigger coefficients the later the Parks' life cycle stage.

The estimates of the *SPwave* and *SPcycle* models, shown at the right end of Table 6, support our hypotheses. The coefficients of the dummies accounting for the waves during which the Parks are created suggest that the younger the Parks, the more effective they are. Furthermore, the SPcycle model suggests that learning happens but very slowly within SPs, as SPs need to get to maturity to become better able to support their tenants. In the SPs' case, experience seems to help but learning processes mainly happen across Parks, rather than within SPs.

7 Conclusions

SPs are organizations that should bridge research and industry and thus enhance the innovativeness and competitiveness of the firms and institutions located on their premises. Whether Parks accomplish their policy mission remains however unclear. The necessity hence arises to further investigate the structure and performance of these regional innovation-supporting loci. The present article does so by providing fresh evidence on SPs' role as seedbeds of innovation. It also sheds light on the role played by firms' characteristics and Parks' features and dynamics in shaping the tenants' innovative performance. The study is somewhat unique in that it contributes to both the traditional SP assessment literature and the US Parks' type one, i.e. the literature focusing on SP characteristics and dynamics vis-à-vis SP effectiveness as policy tools. Besides, the additional elements we gather from the literature on, e.g. innovation and patents, knowledge and knowledge spillovers, and firms' characteristics, contribute to draw a framework mirroring and motivated by the very SP rationale itself.

The analysis we carry out is structured in the form of a duration analysis, where we compare the patenting activity that a sample of firms exhibits before locating inside the SP with the innovative output they show after becoming Parks' tenants. The variance-corrected Cox proportional hazard model we estimate follows Prentice, Williams and Peterson's (1981) conditional risk-set model, estimated in inter-event ('gap') time. It takes care of issues as change of status, censoring and unobserved heterogeneity and holds patenting to be a repeated and event-dependent phenomenon. Our empirical analysis relies on an original dataset regarding the Finnish SPs and a sample of firms that in the year 2002 were located on their premises. The estimates of the 'before-VS-after' hazard rate of patenting feature both time-varying and fixed covariates, which account for some firm and SP characteristics.

We find, as expected, that both firms' size and patents in portfolio positively affect the firms' likelihood to patent. We also find that the years spent elsewhere, before joining the Parks, negatively influence firms' performance, in line with the PLC literature. Finally, sector-related effects emerge, but not persistently, throughout the estimates.

As for the SP-related regressors, we see that the overall number of tenants and the presence of outliers positively influence firms' patenting activity—especially and strongly the last one. Conversely, the presence of Universities seems to negatively affect the hazard rate at which firms patent, at least in the short run. Contrary to expectations, SP's age negatively affects the performance of the tenants. Overall, our results support the hypothesis that spillovers exist within the SPs, with information apparently flowing from big companies to the other tenants. They also point out the existence of non-negligible matching phenomena.

The conflicting evidence emerging from the behaviour of the variables related to being SP tenants (*onoff*) and to the time spent inside the Park (*tinSP*) motivates the robustness checks we carry out. These show the negative effect of the on-SP academic/research centres to be, in the long run, reversed: tenants interacting for a long time with universities should profit from it. We also find SPs' incubators to (extremely) positively affect the innovative performance of those firms joining the Parks when very young. Finally, within-SP learning processes look slow and older Parks seem to suffer from first mover disadvantages. Overall, the robustness checks confirm the existence of strong interactions between firms' and Parks' characteristics, with the tenants' patenting performance being shaped by particular combinations of both. The interaction variables we introduce make the *onoff* coefficient become constantly positive and big in magnitude. Hence, when uncovering some specific interactions, locating inside the SPs seems able to, ceteris paribus, enhance the tenants' likelihood to patent.

Our results shed new light over the SP experience. To begin with we uncover the possible existence of first mover disadvantages, which make pioneer Parks comparatively less effective in constituting seedbeds for innovation. Besides, path dependence seems also to be at stake. SPs look unable to learn and improve their performance over time. Learning mechanisms seem instead confined across Parks, with newcomers learning out of their predecessors' experience.

Such a feature indirectly supports our conjecture about the number of firms located inside a SP not being volatile. Moving is costly for firms and, unless ex-ante agreed upon or otherwise justified, it might be very difficult for Parks to get rid of those companies not benefiting from their SP localisation choice or not contributing to create the 'right' Park environment. Hence, as far as SPs are concerned, being rent seekers might be at odds with the ability to represent effective innovation policy tools, as the latter largely depends on determining the right match SP features—firms' characteristics.

Indeed, an ingredient for the success of SPs is the presence of outliers, thanks to the knowledge spillovers these seem to generate. Universities and research centres located inside the SPs also contribute to enhance the long run innovative performance of the tenants. We manage to capture such a feature thanks to the fact that our analysis considers the lifetime performance of the firms. Would we consider a shorter observational period (as it is often done) we would instead be mislead to believe that HEIs lower the hazard rate of patenting of the firms, as this is what happens in the short run.

In any case, our study does not 'dare' be conclusive. We are aware that, for instance, we have taken a strong stand asserting that selection and self-selection do not impinge upon our results. Although the literature, our analysis of the broader Finnish innovation system and the data we have gathered back our assumption, we know we would be on a much safer ground if we were econometrically able to control for selection and self-selection. Still, we believe our result might contribute to the discussion on SPs and their effectiveness, also vis-à-vis other innovation policy tools. Carrying out this same analysis on a bigger sample and using more covariates might help verifying how general our results are. It would also be interesting to compare the tenants' performance with that of similar 'out-of-Parks' firms and to complement the present study with a patent-quality analysis. We reckon that these, among many others, constitute research paths that might help answering the numerous questions concerning SPs' performance that remain, in fact, still open.

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Appendix

Appendix Table 1A Cox Proportional Hazard Model Variance-Corrected Estimates (Time in Days)

Variables	Model 8 Haz Rat (z)	Model 9 Haz Rat (z)	Model 10 Haz Rat (z)	Model 11 Haz Rat (z)	Model 12 Haz Rat (z)	Model 13 Haz Rat (z)	Model 14 Haz Rat (z)	Model 15 Haz Rat (z)	Model 16 Haz Rat (z)
Onoff	.2469** (−3.74)	.2191** (−3.19)	1.6070 (1.07)	3.6686** (2.06)	1.3435 (0.47)	.7789 (−0.33)	.9442 (−0.07)	5.6472* (1.90)	27.5448** (2.88)
Tenants' characteristics									
Size	1.0004 (1.53)	1.0006** (2.28)	1.0009** (2.57)	1.0010** (3.00)	1.0010** (2.84)	1.0010** (3.05)	1.0009** (2.74)	1.0008** (2.51)	1.0010** (2.40)
Group	1.0641 (0.18)	.9118 (−0.231)	.8225 (−0.56)	.8919 (−0.31)	.8695 (−0.36)	.7589 (−0.77)	.7477 (−0.85)	.70087 (−0.96)	.5743 (−1.23)
Age	.9991** (−3.86)	.9991** (−5.71)	.9990** (−6.60)	.9989** (−6.27)	.9988** (−7.02)	.9989** (−6.81)	.9990** (−6.08)	.9990** (−6.17)	.9989** (−6.45)
Portfolio	1.1544** (3.99)	1.1380** (2.99)	1.2197** (4.69)	1.2334** (4.83)	1.2140** (5.47)	1.1987** (4.81)	1.1740** (4.52)	1.1562** (3.88)	1.1971** (4.19)
Softwareict	.4640 (−1.64)	.4499* (−1.76)	.7345 (−0.58)	.8094 (−0.45)	.5566 (−1.22)	.6353 (−0.98)	1.1804 (0.35)	1.2594 (0.49)	1.1788 (0.29)
Electr	1.9130* (1.73)	1.7809 (1.38)	.9376 (−0.14)	1.0166 (0.04)	.5224 (−1.12)	.3844 (−1.48)	.5325 (−0.87)	.6036 (−0.72)	.3214 (−1.55)
Biotech	.5948 (−0.47)	.6644 (−0.39)	.5542 (−0.66)	.5742 (−0.66)	.3144* (−1.69)	.4588 (−1.24)	.6631 (−0.74)	.6363 (−0.76)	.7791 (−0.44)
SP-related features									
OntinSP		1.0001 (0.46)	1.0003* (1.75)	1.0003* (1.73)	1.0004** (1.99)	1.0004** (2.25)	1.0004* (1.74)	.9988** (−2.93)	.9977** (−3.50)
SPold			.9995** (−3.89)	.9994** (−3.87)	.9993** (−4.09)	.9992** (−3.92)	.9992** (−3.43)	.9992** (−3.42)	.9994** (−2.87)
Uni				.3923* (−1.95)	.3221** (−2.58)	.3009** (−2.55)	.1071** (−3.09)	.0154** (−5.85)	.0147** (−4.01)
Big					6.4987** (3.38)	5.7174** (3.20)	7.6507** (4.26)	7.4223** (4.29)	4.5841** (2.43)
SPsize						1.0093** (2.15)	1.0144** (2.58)	1.0141** (2.56)	1.0174** (3.03)
Incub							.7697 (−0.28)	.8257 (−0.22)	.0149** (−2.72)
SPuni								1.0016** (3.52)	1.0022** (3.22)
Young									64.5949** (3.41)

Model	Number of obs.	log pseudo-likelihood	Wald chi2	Prob > chi2
8	329	−415.11734	113.06	0.0000
9	319	−410.71659	159.86	0.0000
10	315	−383.27548	184.18	0.0000
11	315	−377.52795	158.92	0.0000
12	315	−366.61835	149.57	0.0000
13	315	−360.69684	187.88	0.0000
14	273	−288.22064	156.83	0.0000
15	273	−280.72441	154.72	0.0000
16	273	−262.58883	373.64	0.0000

Breslow method for ties. Standard errors adjusted for clustering on companies

** = significant at 5% level, * = significant at 10% level, z values in parentheses

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