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EIF Research & Market Analysis

Working Paper **2017/45**

The European venture capital landscape: an EIF perspective

Volume IV: The value of innovation for EIF-backed startups

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Luxembourg, December 2017

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Abstract[†]

The creation of value through innovation is among the defining traits of new technology-driven ventures. In this paper we contribute to the literature by investigating the value of innovations for start-ups supported by EIF in the years 1996 to 2014, as measured through patent applications. The paper is structured around two main parts. The first part presents a series of descriptive statistics on EIF's VC investee patent portfolio and discusses some of the strategic aspects of patenting, such as timing and geographical coverage. The second part develops an econometric model to estimate the Euro-value of innovations based on patent renewal data, following the seminal work of Pakes and Schankerman (1984). We observe that start-ups are efficient at transforming financial capital obtained through VC financing into innovative capital. On average, for every Euro of EIF-supported VC financing, start-ups generated 2.74 Euro of private innovation value.

Keywords: EIF; venture capital; innovation; patents; renewal data; start-ups

JEL codes: G24, M13, O32

[†] This paper benefited from the comments and inputs of many EIF colleagues, for which we are very grateful. In primis, we acknowledge the invaluable help of our Research & Market Analysis colleagues Helmut Kraemer-Eis, Antonia Botsari, Andrea Crisanti, Elitsa Pavlova, Frank Lang, Salome Gvetadze and Julien Brault. We are also grateful to Piyush Unalkat for the useful remarks. Moreover, we thank Dario Prencipe for his crucial support during the early days of this work, and Gianluca Tarasconi from Bocconi University for the precious help in analysing the data. Finally, we would like to express our gratitude to Prof. Loriana Pelizzon from Ca' Foscari University of Venice and Research Centre SAFE for her insightful comments. All errors are attributable to the authors.

Non-technical Summary

This work is the fourth volume of the series of working papers entitled "The European venture capital landscape: an EIF perspective". The series aims at assessing whether EIF's VC activity positively affected beneficiary start-up companies, contributing to the broader theme of government intervention in the field of venture capital. This issue is mainly concerned with the innovative capacity of start-ups, tackled via the analysis of patents for 2,951 firms supported by EIF between 1996 and 2014.

Patents are an essential element of the innovative SMEs' toolbox: they not only increase start-ups' competitive position, but also reduce information asymmetries between a start-up and potential investors and thereby act as a signalling device to attract external financing. Against this background, the first part of this paper analyses the patenting behaviour of EIF-backed VC start-ups.

EIF-backed patent production grew at an exponential rate in the years prior to 2001. The crisis induced by the dot-com bubble led to a slowdown in patent growth in the subsequent period. Later, in 2008, an increase in patent renewal fees at the European Patent Office seem to be the driving force behind the significant reduction in start-ups' incentives to patent.

Innovations were predominantly patented by start-ups in the Life Science and ICT sectors, collectively constituting 95 percent of all patent activity. However, innovations from emerging sectors such as Green-Tech gradually gained importance in recent years. The field of oncology emerged as the most active patenting area, followed by research progress in metabolic disorders and electronic devices. The distribution of technology fields remained roughly stable over the entire period considered.

We also note how inventor teams behind EIF-backed innovations have grown increasingly international. However, female participation in patented research remains generally low, with an overall rate just shy of 20 percent, despite significant field-level differences.

VC investees seek to protect their innovation mainly on their domestic market. As such, coverage rates reflect the spatial distribution of EIF-backed VC investees, with about 4 in 5 innovations protected on the European continent. Also the Americas are an important market for European VC investees, reflected in a 65 percent coverage rate of EIF-supported innovations.

The first patented innovation appears, on average, during the first 2 years following company creation. However, often patent registration actually precedes the birth of the company, showing the extent to which the very existence of innovative companies clings on the presence of intellectual property. Interestingly, early patentors also prove to be intense innovators, implying the timing of a start-up's first innovation could provide useful guidance to innovation-minded investors, signalling higher future patent activity. In this context, we note that 56 percent of VC investees' *first* patents are registered before the EIF-backed investment. However, when considering overall innovation count, the statistics revealed that the vast majority of innovations (82 percent) were registered *following* the first investment year. This supports the notion of the dual relationship between VC and patenting, where on the one hand patents function as a signalling device to attract VC funding, and on the other hand VC funding enables start-ups to keep pursuing their R&D targets.

In its second part, the paper employs a patent renewal model based on the seminal work of Pakes and Schankerman (1984) to estimate the private value of innovations owned by EIF-supported VC investees. The value of individual innovations is characterised by a large degree of heterogeneity, with values ranging from just a few hundred Euro to outliers exceeding EUR 400m, with a median and mean of EUR 138k and EUR 2.2m, respectively. Importantly, these findings relate to the *private* value of patent protection, which is to be interpreted as the additional financial return resulting from the patent's protection of the underlying intellectual property. As such, our estimates are likely to represent the lower bound of the total social return, which would include externalities, such as non-appropriable knowledge-spillovers.

A comparison of innovations' values over start-up industries and technology areas reveals that innovations stemming from the life sciences industry are, on average, more valuable than in other innovation areas. However, we also consistently observe that the lower propensity to patent is positively correlated to the "shortage" of low-valued innovations, which may be indicative to stronger barriers to patenting that are known to exist in certain sectors and geographies.

Finally, we compare EIF-supported financing with start-ups' innovative output, producing an "innovation multiplier" linking inputs and outputs of the EIF VC activity. While such indicator bears no virtue of causality, it allows to track the ability of start-ups to transform financial into innovative capital. The analysis shows that for every Euro of VC financing flowing into EIF-backed start-ups, investees were able to create 2.74 EUR of private value via patented innovations. Overall, this work evidences the magnitude of EIF's support to innovation through its VC investments in Europe and beyond.

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1 Introduction

The role of Venture Capital (VC) financing in spurring innovation has been extensively documented in the literature (see Kortum and Lerner, 2001, among others). This is because innovative Small and Medium-sized Enterprises (SMEs), risky by nature, are often unable to secure financing through traditional bank channels and therefore rely disproportionally on VC to meet their external financing needs. Therefore, through its support to the VC ecosystem in Europe (see Kraemer-Eis *et al.*, 2016), the European Investment Fund (EIF) has played a significant role in the development of an ecosystem that enables SMEs to reach their full innovative potential. In this context, this paper analyses the innovative capacity of EIF-backed Venture Capital (VC) start-ups by documenting their patenting behaviour. It constitutes the fourth chapter in the series of working papers titled ”The European venture capital landscape: an EIF perspective”.

The choice to document the innovative capacity of EIF-backed VC investees by analysing their patenting behaviour is motivated by two observations. First, a well-developed patent system ensures innovating firms have an incentive to invest in research and development (R&D), *i.e.* via granting the full ownership of revenues from the commercialisation of patentors' inventions (Cornelli and Schankerman, 1999). Patents serve a second, perhaps less obvious purpose, as start-ups also use them as signalling devices to attract external financing. When a start-up's novel business idea — obscure by nature — is backed by a patent early in its life-time, it will partly alleviate the information asymmetries that typically arise towards potential investors (Conti *et al.*, 2013; Hoenen *et al.*, 2014). Their dual purpose implies that patents have the potential to positively affect the economic value (Helmers and Rogers, 2011) and growth-prospects (Balasubramanian and Sivadasan, 2011) of start-ups.

Evidently, patents are just one manifestation of firms' innovative capacity and our focus on patents does not imply that non-patenting firms are prescribed as non-innovative. Some companies may prefer alternative strategies (*e.g.* industrial secrecy) to preserve their intellectual property (IP). Moreover, some inventions may not be technically patentable, *e.g.* software. In other cases, companies might not want to patent their innovations to ensure maximal diffusion, as is often the case for social innovators.[1] A thorough examination of patents' pitfalls as innovation indicator lies beyond the scope of this work (interested readers can refer to Archibugi, 1992). Nevertheless, it is worth underlining that given the nature of the indicator used in this paper, we can only trace companies whose patenting activity constitutes an optimal strategy to pursue their business and R&D goals. As such, our work cannot be considered exhaustive of all innovative activities undertaken by EIF-backed start-ups.

The paper is structured around two main parts. The first part presents a series of descriptive statistics on the patent portfolio of EIF-backed VC investees. It discusses the evolution of investees' innovative capacity, its sectoral composition, geographic distribution and the composition of inventor teams. It also covers some strategic aspects of patenting behaviour, such as the timing of patent registration and patents' geographical coverage. The second part subsequently estimates the aggregate economic value of EIF-supported patents using data on patent renewal fees, based on the seminal work of Pakes and Schankerman (1984).

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[1] These limitations led to a number of authoritative studies challenging the notion that patent protection systems contribute positively to aggregate innovation. See *e.g.* Moser (2005) and Lerner (2002).

2 Data and methods

Patent data for this study mainly stems from Bureau Van Dijk's Orbis database and originates from the PATSTAT database, maintained by the European Patent Office (EPO). Our initial dataset contains both granted and non-granted patents for 2,951 start-ups supported by EIF in the 1996–2014 period. In line with past works in the series, the data relates to EIF-backed start-ups whose size, age and industry comply with the canons of conventional VC-targeted companies (see Kraemer-Eis *et al.*, 2016).

Patent data is matched with firms' identities following the methodology outlined in Thoma *et al.* (2010). The matching strategy is based on a statistical model employing a similarity index of applicant names. As such, matching errors may occur, both of type I (*i.e.* the incorrect assignment of patents unrelated to the company, also known as "false positives") and type II (*i.e.* the incorrect rejection of pertinent patents, also known as "false negatives"). With regards to false positives, we consider the likelihood of this event to be negligible. Nevertheless, we discard patents whose initial date of application falls more than 15 years behind the firm's establishment date — on the assumption that start-ups have no incentive to protect and exploit innovations very close to fall in the public domain.

With regards to false negatives, we observe that for a noteworthy innovation to be incorrectly discarded, all its associated patents (typically numerous) would have to be jointly discarded too. For this reason, we assume the chance of false negatives to be negligible. However, since each patent provides insights on the total innovation value (see section 4), we may be interested in the "coverage rate" of our dataset, measured in terms of *matched patents* (from Orbis-PATSTAT) over total patents available in the family (from EPO-PATSTAT). Based on a random sample of 479 patent families, we estimate such coverage to lie between 73% and 81%, high enough to allow for meaningful results.

We select patent families as our main proxy for innovations. The EPO defines a patent family as *"a collection of related patent applications that is covering the same or similar technical content"*, as well as *"a collection of patent documents that are considered to be covering one single invention"* (European Patent Office, 2017).[2] As such, patent families are regularly employed as unit of analysis when the research focus is on firms' inventions (Hall, 2014). For additional details on the notion of patent families, see Martinez (2010).

On the basis of such proxy, we find a total of 16,155 unique innovations associated to EIF-backed start-ups and initiated in the period 1977 to 2015.[3] However, consistent with similar works on patent data we discard innovations initiated after 2012. This decision follows the time lag — up to 30 months for EPO data[4] — between the date of application and the time of publication in the PATSTAT database, which drives the decrease in number of innovations observed in the latest years. The narrower time frame causes a reduction to the number of analysed innovations, down to 14,292.

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[2] The EPO actually employs two definitions of patent families: the DOCDB *simple* patent family and the INPADOC *extended* patent family. The second definition encompasses "a technology [. . .], and will generally contain more than one invention" (EPO, 2017, p.22). For such reason, and due to the fact that at the time of the analysis the EPO API did not provide INPADOC identifiers, we favoured the former definition.

[3] The figure does not account for utility models and designs, excluded from the analysis. In addition, note that the initial year of the innovation typically equates to the *priority year* of its underlying patents.

[4] Additional delay is most likely introduced by the subsequent matching with firms' identities.

This work employs patent family *ownership*, as opposed to *registration*, as the main unit of analysis. The key difference is that the former can be transferred between entities following acquisition of companies and/or their intellectual property (IP) portfolios. Based on historical data on patent applicants, we can infer that about 86 percent of innovations owned by EIF-backed start-ups were also registered by them.[5] However, depending on the nature of the analysis the distinction between *acquired* and *originated* IP may be irrelevant, as the two R&D strategies can be equally effective in the creation of new innovative capacity for the firm. In general, we note that a given analysis may be best suited for a specific subset of the data. Against this background and the multitude of sample subsets used in this work, Table 1 breaks down the initial dataset and links each subset to its respective section(s).

Table 1: Patenting of EIF-backed start-ups: sample breakdown

	Innovations		Start-ups		
Sample description	Nr.	Time frame	Nr. (patentors)	Inv. time frame	Ref. section(s)
Initial dataset	16,155	1977–2015	2,951 (1,080)	1996–2014	
of which:					
excluding patenting after 2012	14,292	1977–2012	2,359 (984)	1996–2012	2
of which:					
patenting while in EIF portfolio	11,571	1996–2012	2,359 (875)	1996–2012	3.1–3.4
in-house patenting	12,335	1977–2012	2,359 (942)	1996–2012	3.5
of which:					
while in EIF portfolio	10,098	1996–2012	2,359 (840)	1996–2012	3.6
patenting with renewal data info†	11,597	1987–2012	2,359 (984)	1996–2012	4

† Only partial renewal data information could be retrieved for some innovations. See section 4.2 for details.

Several features of EIF-supported innovations complement our firm-patent matched dataset. These are formed via aggregation of patent-specific characteristics at the level of the patent family, using the most appropriate technique. Notably, using the International Patent Classification (IPC) system we grouped innovations into 9 different sectors — following the 2007 sectoral classification of Invest Europe[6] — according to the most frequent sector observed in the underlying set of patents (for additional details on this approach see Appendix A). Moreover, we used the location of patent offices receiving applications for a given innovation to derive a set of geographic indicators. These variables identify the geographic breadth (*e.g.* Europe, America, Asia) of patented innovations.

In addition, significant data work was dedicated to the retrieval of attributes related to the patenting team: based on patentor full names and nationality, we created a set of indicators describing the rate of internationalisation as well as the gender distribution of patenting teams.[7] Finally, motivated by the impracticality of identifying innovation fields via the IPC system, we devoted further effort to the detailed analysis of patent abstracts (for details see Appendix B). This exercise allowed the classification of innovations into 20 key technology fields, providing a granular yet intuitive classification of the key technology areas supported by EIF throughout the last 20 years.

5 For the remaining 1,957 innovations, current ownership did not coincide with the original applicants. It ensues that these innovations were acquired by EIF-backed start-ups. Interestingly, the ownership of about 38 % of acquired innovations further transitioned to other entities, following either the acquisition of the start-up or its bankruptcy.

6 Available at http://www.investeurope.eu/media/12926/sectoral_classification.pdf [accessed: 11/2017].

7 Gender likelihood is based on first names and countries and was obtained from genderize.io. The API provides gender likelihood based on a sample of individuals from the specified nation. Against this background, the gender likelihood was validated if above 70% and based on at least 30 individuals. Patenting teams reporting less than a third of their members' genders were excluded from the analysis.

3 Patent analysis of EIF-backed VC investees

3.1 Innovative capacity of EIF-backed start-ups

While VC investees are almost by definition assumed to be innovative, not all of them engage in production activities that require patent registration. Of the 2,359 firms receiving EIF support through venture capital between 1996 and 2012, 42 percent owned one or more patented innovation. In total, 11,571 innovations were patented or acquired either during or following EIF-backing, by 875 VC investees. To narrow our focus on just those innovations that are rooted in EIF-support, the descriptive analysis in this chapter will consider only the latter group, unless otherwise mentioned.

Figure 1 contains four subpanels which together provide a detailed overview of the evolution of the innovative capacity of EIF-backed VC investees. Patent growth (Figure 1a) can derive from changes in three subfactors. First, it can be rooted in numbers and hence will be positively correlated with the size of EIF's VC portfolio, all else equal (Figure 1b). Second, it can be driven by changes in the innovation propensity of investees at the extensive margin, that is, the share of investees that engage in patenting activities (see Figure 1c). Third, innovation propensity can also change at the intensive margin, when patenting investees increase the intensity at which they are patenting (Figure 1d). Distinguishing between these three driving factors can provide additional insights in the evolution of the innovative capacity of the EIF-backed VC portfolio.

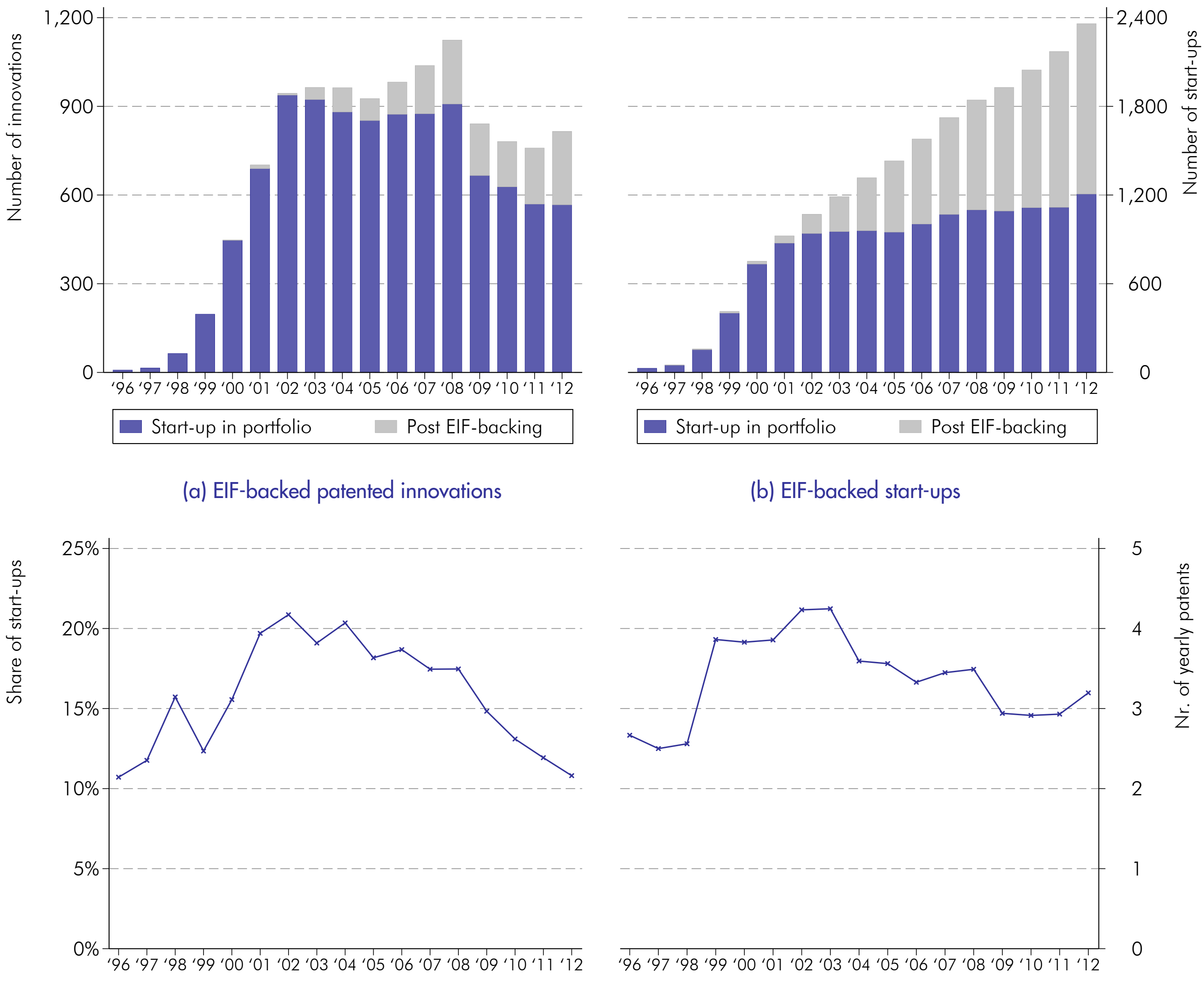
Initially, the number of EIF-backed innovations grew exponentially from just 8 in 1996 to 944 in 2002. Innovation growth during that period was rooted in sheer numbers, as it was driven by a substantial increase in the size of EIF's VC portfolio, which by and large followed a similar trend (see Figure 1b).[8] However, another driver was at play. While the share of patenting EIF-investees did not follow a pronounced trend over that specific period (see Figure 1c), patent intensity almost doubled from 2.66 to 4.23 patents per year (see Figure 1d). With the exception of the abrupt drop between 2008 and 2009, innovation production stagnated until 2012. Meanwhile, the EIF VC portfolio continued to grow. Figure 1c and Figure 1d bring to light how these divergences were due to a decline in innovation propensity, mostly at the extensive, but also at the intensive margin. The share of start-ups engaged in innovation declined from 2006 onwards, dropping to 10.8 percent in 2012.

The sudden drop in innovative capacity between 2008 and 2009, when innovation production dropped from 1,124 to 841. It is only natural to link such drop to the onset of the financial crisis. Indeed, past literature highlighted the pro-cyclical nature of R&D expenditure, both at the micro (Archibugi *et al.*, 2013) and macro (Izsak *et al.*, 2013) level. However, Izsak *et al.* (2013) also note that for most EU countries this decline took place on the background of growing or stable R&D inputs.

Against this backdrop, one additional key factor for the drop in patenting rates may have been the 2008 policy change implemented by the EPO, who undertook a revamping of the fee structure for patent applications. The decision aimed at curbing the growing volume of applications, not all of which were considered to be valuable or innovative. The added patenting expenses significantly decreased firms' incentives to register and protect their innovations, reducing the administrative burden from excessive patent applications faced by the EPO (Harhoff, 2016).

8 See Kraemer-Eis *et al.* (2016) for a detailed analysis on the growth trends in EIF's VC portfolio.

Figure 1: Evolution of innovation creation by EIF-backed VC investees[9]



(a) EIF-backed patented innovations

(b) EIF-backed start-ups

(c) share of EIF-backed patentors

(d) average patents per patentor

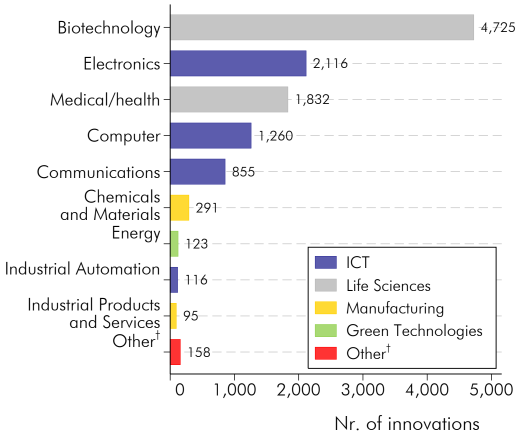
3.2 Innovation by sector and technology field

Figure 2 shows that innovation is heavily concentrated in just two sectors:[10] nearly 95 percent of EIF-support innovations were owned by investees operating in the sectors of Life Sciences (56.7 percent) and ICT (37.6 percent). Figure 2b graphs how the sectoral distribution evolved between 1996 and 2012. While initially all innovations originated in the Life Sciences and ICT sector, other sectors gradually gained importance over subsequent years. Notable trends are the growing importance of manufacturing innovation from 2000 onwards and the rise of the Green Technology sector in most recent years, with the latter trend likely reflecting a shift in European policy priorities.

[9] Unless otherwise stated, all figures in this research are an elaboration of the authors, based on EIF data.

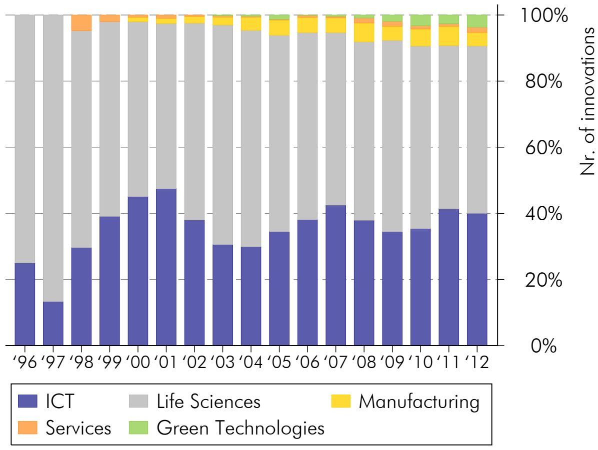
[10] For reasons of comparison, this section proceeds with the sectoral classification used in Kraemer-Eis *et al.* (2016), which distinguishes between 5 aggregate start-up sector classes: Life Sciences, ICT, Manufacturing, GreenTech and Services. Signore (2016) further details the sectoral distribution of the EIF VC portfolio.

Figure 2: Innovation by start-up industry



†Consumer goods/services (78); Manufacturing (other) (58); Services (other) (20); Construction (2).

(a) innovations by start-up sector



(b) evolution of macro-sector distribution

Perhaps more interesting than the sectoral distribution of EIF's VC investees are patents' technological focus areas. In contrast to the sectoral classification, which is a characteristic of the innovating firm, technological focus is innovation-specific. Hence, patenting in a given technological field can occur by investees from different sectors. Traditionally, patents are classified according to the International Patent Classification (IPC), a hierarchical system that was constructed to facilitate the search for patents by classifying them according to different areas of technology. Although useful for administrative purposes, the complexity of the matter makes that the IPC classification lacks intuitive appeal for the purpose at hand. The top level of the IPC contains 8 'sections', each pertaining to the broader field in which the patented technology is applied. Going one level beyond the top of the IPC hierarchy drastically increases the number of categories and immediately results in 130 different 'classes', resulting in a level of granularity that is unworkable. Therefore, this section builds on the classification strategy introduced in section 2, based on patents' abstracts.[11] This method led to the construction of 20 distinct innovation categories, as illustrated in Figure 3.

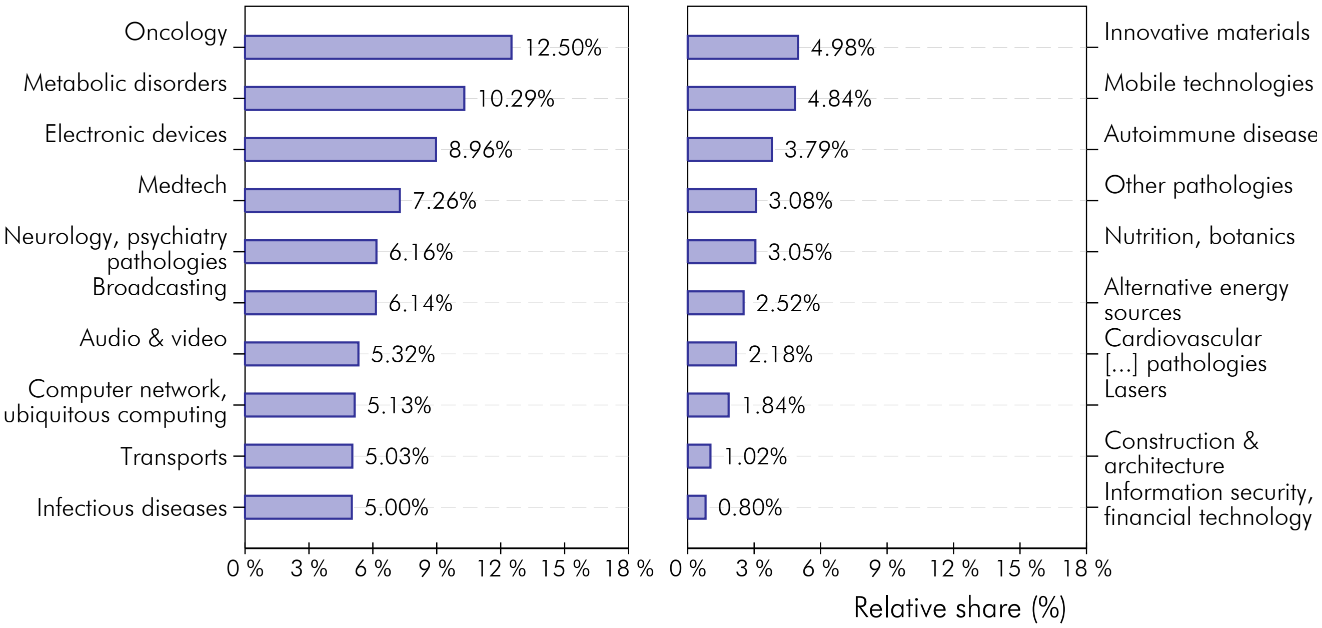
EIF supported innovations across a wide array of innovation fields, the most popular one being Oncology (one in eight innovations). The second most supported field was Metabolic disorders, followed by Electronic devices and Medtech. Figure 4 plots how the distribution changed by comparing frequencies over time. While Oncology ranked as the most popular field over the entire period considered, it lost some of its relative importance in recent years. The same holds true for Medtech and Transports. On the other hand, innovation shares in the fields of Neurology, Mobile technologies, Other pathologies and Nutrition significantly increased. For the remainder, the distribution of technology fields stayed roughly constant.

3.3 The geography of EIF-backed innovation

Table 2 illustrates the geographical distribution of EIF-backed patents. It follows the regional classification proposed by Kraemer-Eis *et al.* (2016) and aggregates investees' innovations to eight macro-

[11] For an elaboration on the methodology, see Appendix B.

Figure 3: EIF-supported innovations, by technology field



Note: based on a sample of 7,685 innovations from 799 start-ups supported by EIF with complete innovation field data.

regions.[12] The data is analysed using the same approach as in Figure 1 and the total number of innovations per macroregion is decomposed into three sub-factors: the total number of investees (column 3), the share of those investees engaged in patenting (column 4) and the average number of innovations owned by each of the patentors (column 5).

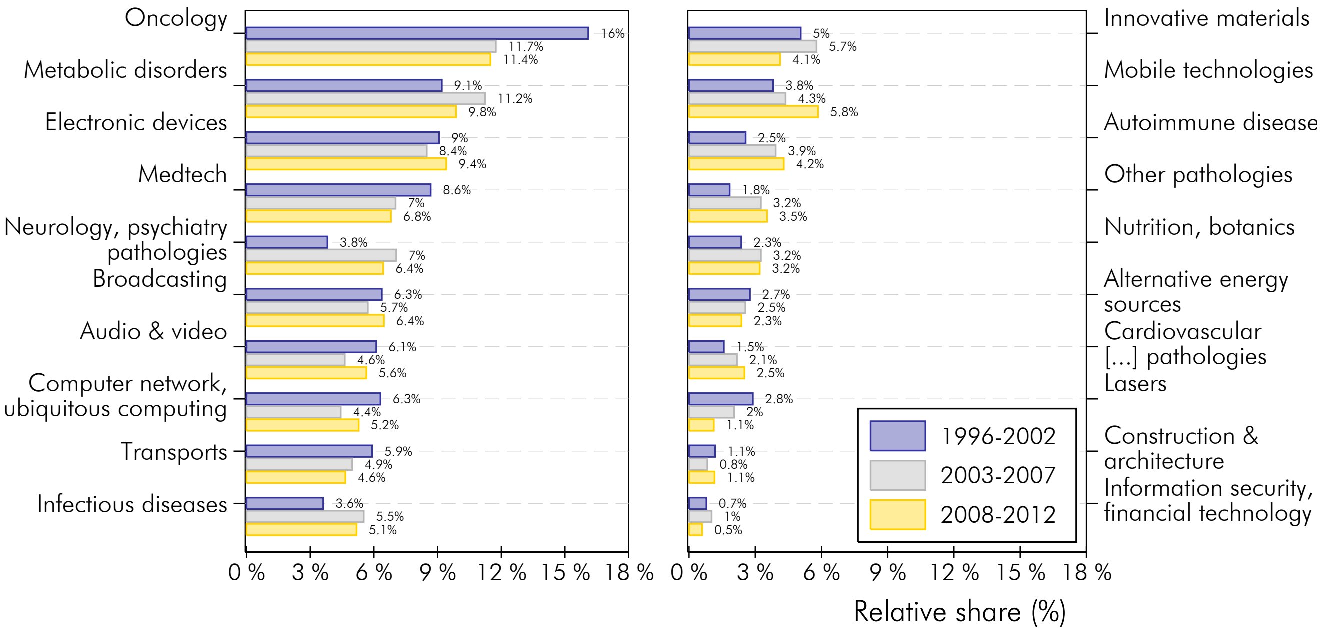
EIF's patent portfolio benefited most from the contribution of investees from the British Isles (BI), which account for one third of innovations. The region with the second largest innovative capacity is FR&BENELUX, closely followed by DACH. Investees from the North-American region (N-AM) supply the bulk of innovations originating outside of Europe. Noteworthy is the rather modest contribution from the CESEE and SOUTH regions.

Table 2: EIF-backed innovations per macroregion

		Sub-factor		
Macro-region	EIF-backed innovations	EIF-backed start-ups	Share of patentors	Average nr. of innovations per patentor
British Isles	3,843	574	42.16%	15.88
FR&BENELUX	2,593	565	34.33%	13.37
DACH	2,383	468	40.38%	12.61
N-AM	1,638	187	49.19%	17.80
NORDICS	850	251	43.42%	7.80
SOUTH/CESEE	137	276	13.04%	3.81
ROW	127	38	34.21%	9.77

[12] DACH: AT, CH, DE; NORDICS: DK, FI, NO, SE; FR&BENELUX: BE, FR, LU, NL; SOUTH: GR, ES, IT, MT, PT; BI (British Isles): IE, UK; CESEE: BG, CZ, EE, LT, LV, PL, RO, SK, TR, CY; N-AM: US, CA; ROW (Rest Of the World): AR, AU, CN, CR, HK, IL, IN, MX, PH, RU, SG, UY.

Figure 4: Evolution in the distribution of innovations by technology field



Note: based on a sample of 7,685 innovations from 799 start-ups supported by EIF with complete innovation field data.

While to some extent the differences in regional innovative capacity are rooted in the unequal regional distribution of EIF investees, the innovative capacity of VC investees also differs significantly between regions. In the N-AM and NORDICS regions, almost one out of two EIF-backed investees own at least one patented innovation, compared to just 13 percent in SOUTH and CESEE combined. The latter two regions also close the rankings when considering innovative capacity at the intensive margin: patenting investees in CESEE and SOUTH produced on average 3.8 patented innovations. N-AM outperforms the other regions with an average of 17.9 patented innovations per innovating investee.

Although Table 3 shows that Life Science is the most dominant sector over all macroregions considered, the extent of its dominance varies significantly, ranging from just shy of 50 percent of total innovations in the British Isles to 66 percent in N-AM. Investees from BI excel in ICT-based innovations (45.4 percent). This contrasts with the DACH region, where the ICT sector accounts for for just 28.3 percent of patented innovations. Also note the relatively high shares of manufacturing-based innovation in DACH (8.6 percent) and Green Technologies in SOUTH and CESEE (8 percent).

Table 3: Sectoral distribution of innovations per macroregion

	Start-up macro-sector				
Macro-region	ICT	Life sciences	Manufacturing	Services	Green-Tech
British Isles	45.43%	49.85%	2.73%	0.67%	1.30%
FR&BENELUX	38.71%	56.99%	2.81%	0.77%	0.69%
DACH	28.32%	60.17%	8.64%	1.00%	1.84%
N-AM	32.78%	65.68%	0.85%	0.67%	0%
NORDICS	33.64%	59.88%	4.58%	1.88%	0%
SOUTH/CESEE	36.49%	50.36%	4.37%	0.72%	8.02%
ROW	38.58%	59.05%	2.36%	0%	0%

Table 4 lists the 5 most popular technology fields by macroregion. While oncology appears in the top 5 of all depicted regions, its relative popularity is highest in North America (N-AM) and the FR&BENELUX region, covering 16.04 and 16.67 percent of all innovations, respectively. In general, the concentration of patenting in specific technology field is significantly higher in N-AM, FR&BENELUX and to a lesser extent DACH compared to other regions.[13]

Table 4: Most frequent technology fields by macroregion (relative frequency in brackets)

	Macroregion				
Ranking	British Isles	DACH	FR&BENELUX	NORDICS	N-AM
1	Broadcasting (11.44%)	Oncology (12.6%)	Oncology (16.67%)	Neurology, psychiatry pathologies (9.01%)	Oncology (16.04%)
2	Electronic devices (10.45%)	Metabolic disorders (10.04%)	Metabolic disorders (12.91%)	Oncology (9.01%)	Metabolic disorders (14.18%)
3	Oncology (8.42%)	Electronic devices (8.99%)	Electronic devices (12.21%)	Electronic devices (8.31%)	Medtech (9.12%)
4	Metabolic disorders (7.15%)	Medtech (8.1%)	Medtech (8.85%)	Metabolic disorders (7.62%)	Neurology, psychiatry pathologies (6.58%)
5	Computer network, ubiquitous computing (7.1%)	Infectious diseases (6.74%)	Innovative materials (5.9%)	Medtech (7.45%)	Infectious diseases (6.33%)
Sample size	2,124	1,912	1,727	577	1,184

Note: For reasons of representativeness, only regions with at least 100 innovations providing technology fields are shown.

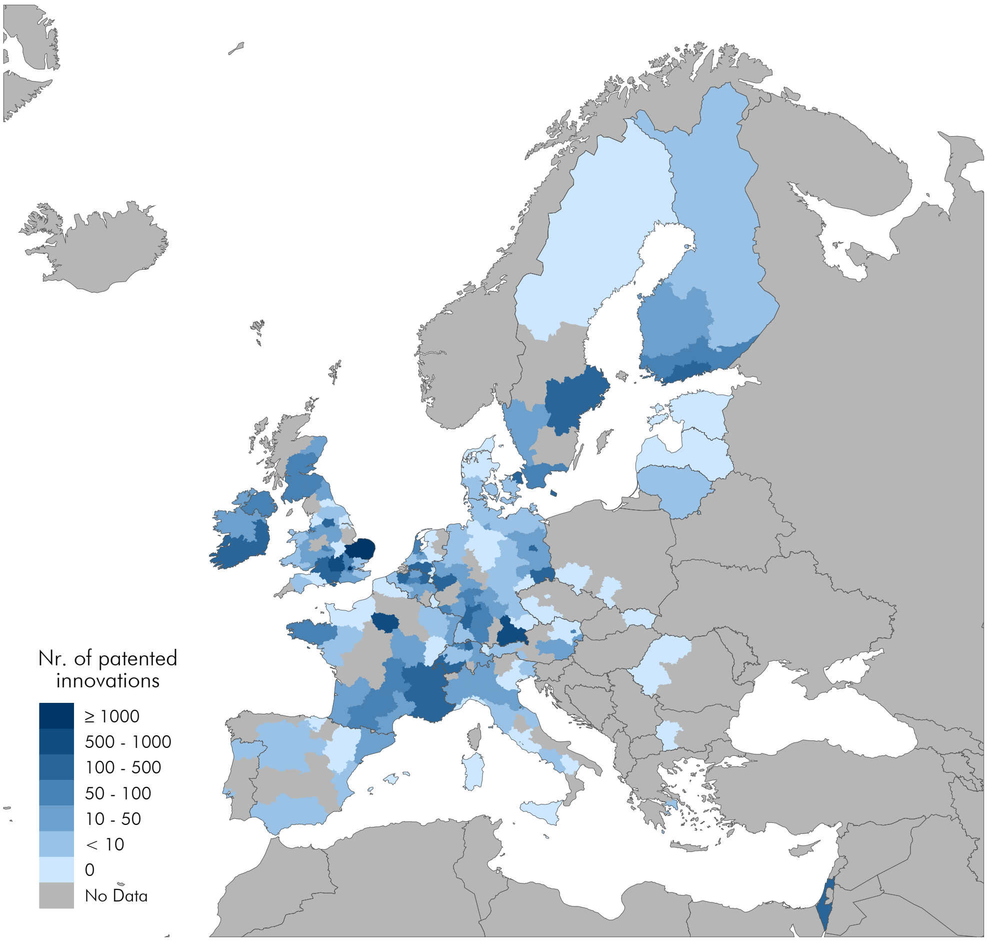
Figure 5 takes advantages of the high level of granularity in the data to examine in more detail the geographical patterns that are present in innovation activities. The map reveals that innovation activity is concentrated in a limited number of regions, primarily along a heavily urbanised area that stretches from Manchester, over the North of Belgium and South of the Netherlands, through South-West Germany all the way to Milan. The pattern exposed in Figure 5 is consistent with earlier studies on the positive relationship between urbanisation and innovation (see Lobo and Strumsky, 2008; Bettencourt *et al.*, 2007, among others).

3.4 Patents' geographical coverage

Traditionally, the coverage of a patent was limited to the issuing country, so that acquiring extended geographical protection of an invention was a cumbersome and costly task. The introduction of international patent offices such at the EPO and WIPO has greatly facilitated expanding an innovation's geographical protection radius. However, geographical expansion still comes at a price and therefore not all innovations will seek global coverage. Patents will generally only cover those areas for which investees believe there is a market for their goods. Therefore, the findings below provide an indication on the importance of the respective continents for VC investees' expected product demand.

[13] A back of the envelope calculation of a simple Herfindahl index of concentration confirms this.

Figure 5: Regional distribution of EIF-supported innovation at the NUTS2 level



Note: based on a sample of 11,030 innovations and 1,966 start-ups supported by EIF with complete geographic data.

Figure 6 illustrates how EIF-backed innovations are protected across different continents. An innovation is counted as covered in a certain continent if its patent covers at least one country belonging to the continent's territory. About 4 in 5 innovations cover Europe. The second most popular market for investees to seek protection is the American continent (65 percent), followed by Asia (41 percent) and Oceania (27 percent). Unsurprisingly, VC investees are least concerned about copyright infringements on the African continent, where the coverage rate is just 4 percent.

Evidently, these findings partly reflect the spatial distribution of VC investees. European investees will often focus their efforts on the domestic market, and hence will therefore only seek patent coverage locally. To gain some deeper insight into the geographical reach of patent protection, Table 5 disaggregates geographical coverage rates by macroregion. As expected, the graph reveals a strong correlation between an investee's location and the geographical coverage of its patents. North American VC investees choose to protect their innovations on the American continent at a much higher rate than European investees, and vice versa. Somewhat surprising, the graph also reveals that the American market appears to be less relevant for British than for continental-European VC investees.

While European VC innovations are in general well protected on European markets, domestic coverage rates are still well below 100 percent. Around 1 in 5 innovations from VC investees located in the DACH region, for example, did not seek protection on any European market. Presumably, these innovations belong to European VC investees that are export-oriented.

Figure 6: Geographical coverage of innovations' patent protection

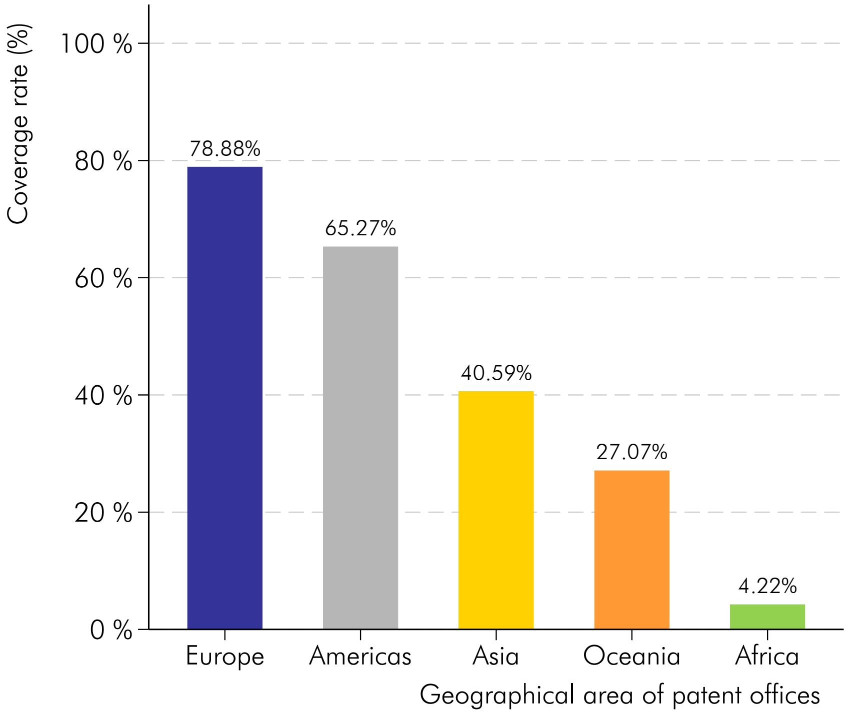


Table 5: Geographical coverage of innovations' protection by start-up location

	Area of IP protection				
Macro-region	Europe	Americas	Asia	Oceania	Africa
British Isles	89.04%	56.04%	34.68%	20.01%	3.66%
FR&BENELUX	82.06%	71.53%	49.47%	29.61%	6.09%
DACH	83.29%	61.64%	40.11%	30.71%	3.39%
N-AM	46.64%	81.25%	37.36%	34.73%	4.02%
NORDICS	77.73%	65.37%	44.99%	28.38%	4.24%
SOUTH/CESEE	80.29%	65.69%	42.33%	16.78%	0.72%
ROW	45.66%	77.16%	57.48%	23.62%	4.72%

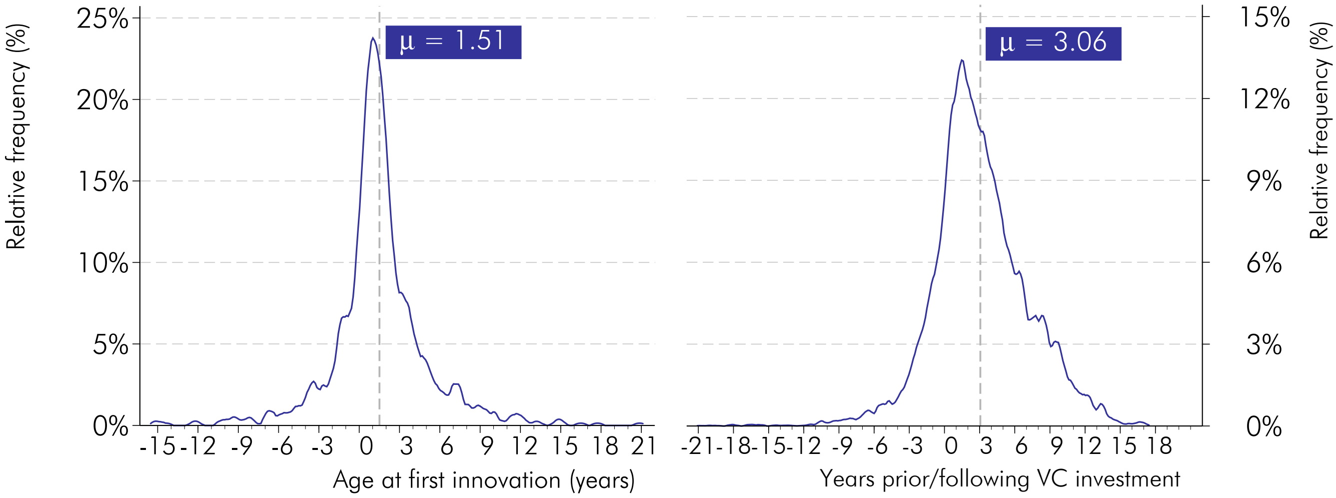
3.5 Timing of innovation

This section takes an in-depth look at the timing of innovation. It analyses in which phase of their life or investment cycle VC investees are most likely to innovate and how innovation timing differs between technology fields and sectors. The outcome of the timing analysis is likely to be connected to the technological processes underlying investees' innovation activities. To restrict the focus on the research teams of EIF-backed start-ups, we consider only those innovations stemming from "in-house" innovation activities. We therefore omit 1,957 patented innovations that were acquired by EIF-backed start-ups, as discussed in section 2. This leaves 12,335 in-house innovations.

Figure 7a illustrates the distribution of the age at which investees register their first innovation. A negative value implies an innovation was registered before the company was founded. Negative values are relatively common: 142 investees patented their first innovation before they went on to create a company. Yet, most start-ups register their first innovation after company creation, a significant number of them in the year of creation itself (265) or in the year thereafter (208).

The timing of patent registration *vis-à-vis* company age can be a useful indication of future patenting activity. The older the investee at the time of first patent registration, the less intensely it will patent during its post-investment lifespan. An investee that registers its first innovation before its company was legally established on average innovates at a rate of 1.80 patents per year during its post-investment life span. For start-ups that patented their first innovation only after the establishment of the company, this drops to 0.97 patents per year.

Figure 7: The timing of start-up innovation



(a) age distribution at first innovation

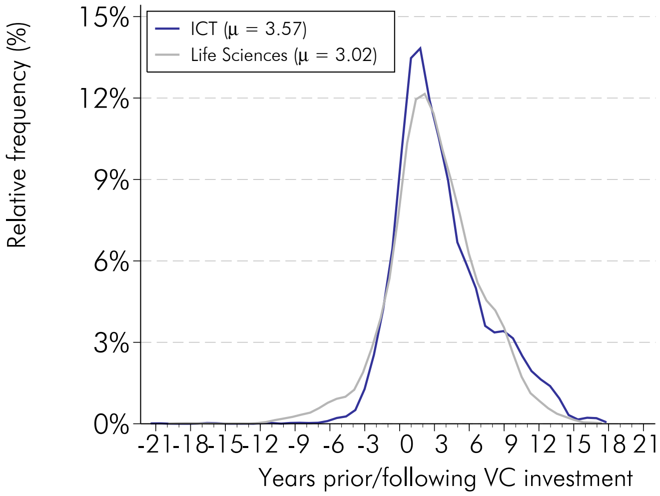
(b) patent submission compared to VC investment date

After having illustrated the timing at which investees start to innovate, Figure 7b depicts how fund managers time their investment *vis-à-vis* in-house innovation production of their investees. The histogram shows how patent registration is distributed around the vintage year. The pronounced jump in patent registrations in the first 2 years following the vintage year indicates the importance of VC funding for the innovation process. Investees register the vast majority of their in-house innovations (82 percent) after they received VC backing, indicating that VC can encourage the patenting of in-house innovation. Interestingly, however, when considering only the first patented innovation, 56 percent of innovations are registered *before* VC backing. This then points towards the dual purpose of patents, which can also serve as signalling devices to attract external financing.

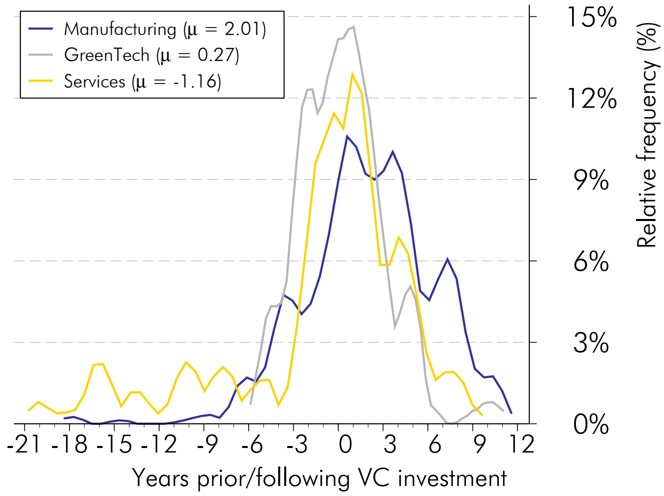
Figure 7b shows furthermore that the tendency to file for patents significantly decreases over time. On the one hand, this finding may be driven by start-ups entering the commercialisation phase, following the achievement of a fully developed patent estate. On the other hand, results may be indicative of the diminishing returns to R&D predicted by endogenous growth theory (Jones, 1995; Klette and Kortum, 2004). The average time span between patent registration and first investment year is 3.06 years.

Figure 8 disaggregates the distribution of in-house innovation production by sector. For investees from the ICT sector, Life Sciences and Manufacturing, VC funding appears to function as a push-factor for innovation, with patent registration increasing significantly during the period immediately following the vintage year. Innovation timing of investees from the GreenTech sector look different, as innovation registration spikes two years *prior* to the first investment year. Hence, in the Green Tech

Figure 8: The timing of start-up innovation, by macro-industry



(a) ICT and Life Sciences



(b) Manufacturing, Services and GreenTech

sector, innovation appears to function more as a quality signal for fund managers. Also in Services innovation registrations spike during the year prior to the first investment year, although the smaller sample size (24 patentors) renders it difficult to draw any definite conclusion.

3.6 Team characteristics: internationalisation and gender balance

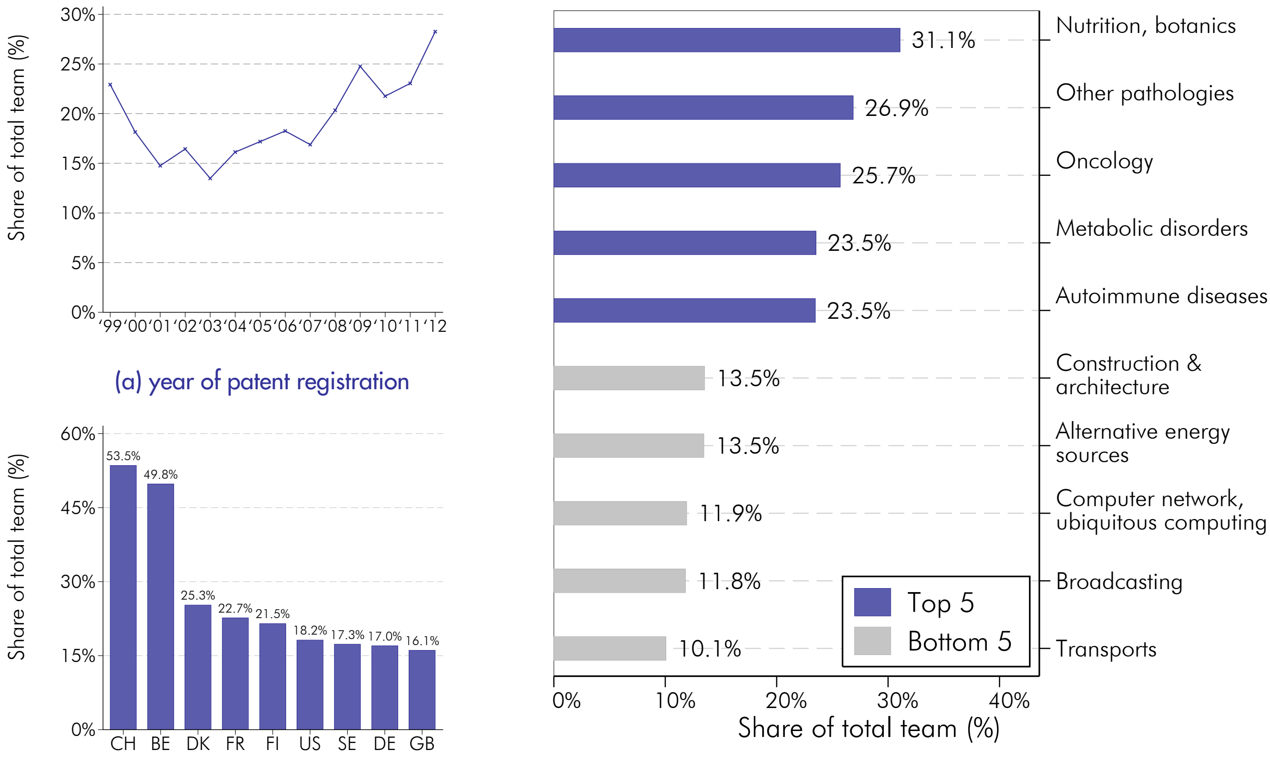
We conclude this chapter with a brief look into two key aspects of patentor teams: internationalisation and gender balance. Patentor teams are defined as the set containing all *unique patentors* in a given start-up and time frame. For the purpose of this analysis, a *patentor* is characterised by a unique set of country, first name and family name.[14] As in section 3.5, we restrict the focus to "in-house" innovations, further omitting pre-investment data to limit the capturing of inventors not affiliated with the start-up. This leaves 10,098 in-house innovations patented by 840 investees.

Research teams of EIF-backed start-ups have become increasingly international. Figure 9a illustrates this by plotting the share of international inventors in patenting teams over time. The share of international patentors was just 14.8 percent in the early 2000s.[15] This percentage steadily increased and hovered around 25 percent since 2008. Start-ups' reliance on foreign scientific personnel differs significantly between countries (Figure 9b) and appears partly correlated with the size of the locally available labour pool: large economies (*e.g.* US, DE, GB) rely mostly on local labour, ranking lowest with around 17 percent of teams having a mix of national and international researchers. For a small open economy like Switzerland, this percentage increases to almost 54 percent, indicating their reliance on foreign scientists to support local production of innovation.

[14] This avoids double counting if the start-up engages in multiple patented innovations. However, we may overestimate the size of patentor teams should any of the patentors not be in the start-ups' workforce (*e.g.* because s/he is employed in a partner company/institution). Moreover, while we correct for small differences, any significant difference in the spelling of names is likely to introduce further upward bias.

[15] The high value in 1999 is misleading, driven by the smaller sample size and the presence of three outliers.

Figure 9: The internationalisation of inventor teams



(a) year of patent registration

(b) start-up location

(c) technology field

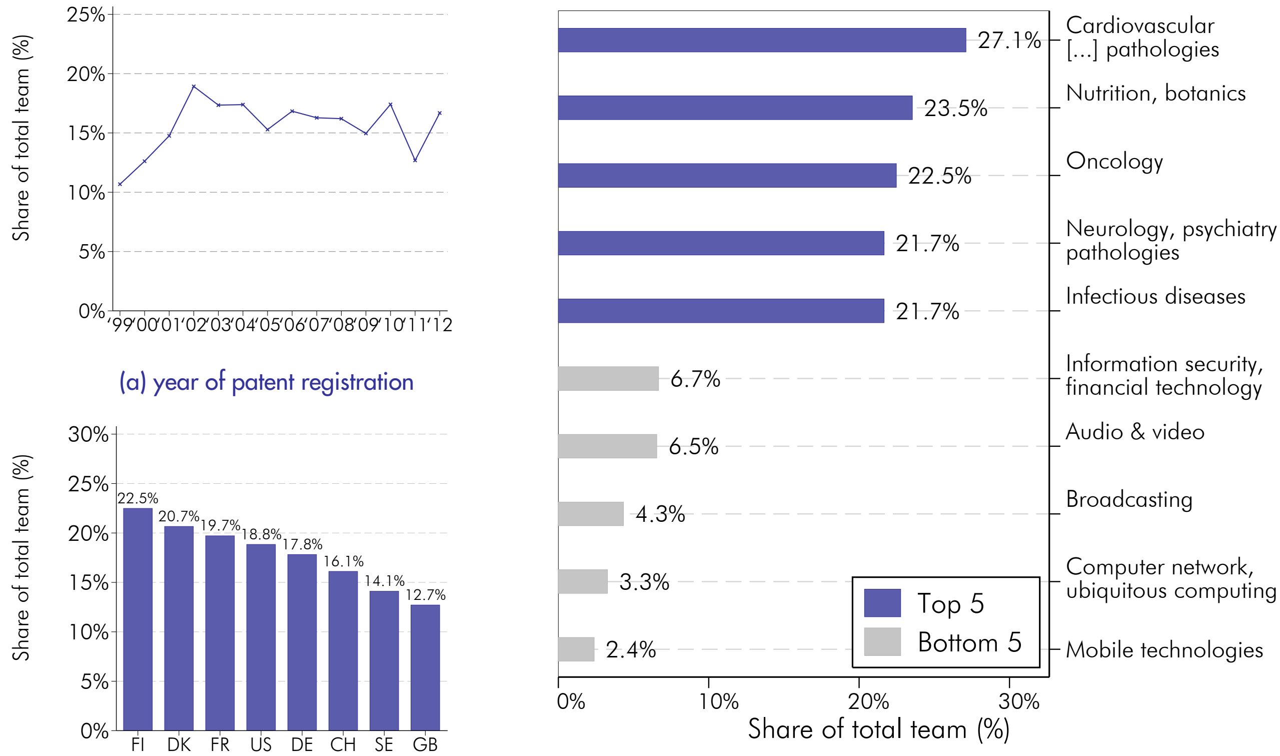
Internationalisation differs strongly across technology fields (Figure 9c), with high levels of internationalisation recorded for innovations in human health related fields (*e.g.* Nutrition, Oncology) and a relatively low level of internationalisation in ICT and Manufacturing-related innovations (*e.g.* Computer networks, Broadcasting, Transports).

The gender balance in start-ups' patentor teams has not followed the expansionary trend of internationalisation rates. Figure 10a illustrates the share of female participation in inventor teams. However, it features similar heterogeneity levels across technology fields. In particular, we observe a similar dichotomy as the one featured by internationalisation rates (Figure 10c): on the one side, teams in ICT-related fields are strongly male-driven, with the percentage of women not exceeding 6 percent. On the other side, female participation rates in Life sciences typically surpass the 20 percent share. While the gender gap is significantly smaller for health-related fields, it hardly exceeds 30 percent, let alone reach parity. Expectedly, we also observe significant country-level differences: 22.5 percent of inventors behind Finnish innovations were female, compared to the average participation of 13 percent in the United Kingdom.

4 The economic value of start-ups' innovations

A key limitation with unit counts of patent families — so far the selected indicator to gauge the importance of patenting for VC-backed start-ups — lies in their representation of innovations as homogeneous units of R&D output. This contrasts with the long-standing notion that only a very small subset of innovations is able to yield significant returns, with most others falling short of the

Figure 10: The gender distribution of inventor teams



(a) year of patent registration

(b) start-up location

(c) technology field

average (Shepherd, 1979). Against this backdrop, the remainder of this paper is concerned with the estimation of the private economic value of patented innovations produced by EIF-backed start-ups.

In the past, the need for robust estimates of the economic value of patents emerged in various contexts. At the microeconomic level, the knowledge of a company's own IP portfolio is essential to undertake sound management decisions related to, *e.g.*, IP protection and return strategy. In addition, an increasing number of firms reportedly use IP as a means to access external financing, *e.g.*, venture capital and bank loans (Kamiyama *et al.*, 2006). At the macroeconomic level, patent value estimates can prove useful for public policy makers to refine their understanding of the innovation process. This in turn stimulates the search for better policy to support the innovative capacity of firms.

In his early review of patent valuation methods, Pitkethly (1997) discusses several different methodologies to derive *ex-ante* estimates of patent values. These approaches — leveraging on cost-, market-, discounted cashflow- and option pricing-based models — are considered appropriate to estimate the value of single patents, requiring in-depth information on the envisaged exploitation of the underlying IP.[16] Alternatively, Pitkethly mentions a class of valuation strategies — referred to as *econometric methods* — concerned with the *ex-post* measurement of a patent's worth. This latter approach is often based on the stock market values of firms and/or patent renewal rates.

An attractive feature of econometric methods for patent valuation is that these allow to assess the value of numerous patents at once, *e.g.*, patents pertaining to a specific industry, cohort, geograph-

[16] We considered implementing a full-fledged real option pricing model (see *e.g.* Schwartz, 2004). However, the data at our disposal could not satisfy the level of granularity and specificity required by such approach.

ical region. However, Pitkethly notes that early implementations of this approach, based on the seminal work of Pakes and Schankerman (1984), lacked the ability to estimate the value of single patents, but could only provide insights on the overall distribution of patent values. As a result, recent works in the field, most notably Bessen (2008) and Gupeng and Xiangdong (2012), extended Pakes and Schankerman's framework and enabled the estimation of the expected economic value for any single patent, conditional on its renewal pattern, patentor and patent attributes.

In this paper, we propose a simplified model of patent renewal and value based on Bessen (2008) and Gupeng and Xiangdong (2012). We employ this methodology to estimate the value of patent families linked to EIF-backed start-ups, a proxy for their innovative capacity. The estimates concern the *private* value of a patent, calculated as the (net present) value of all profits a start-up gains from exercising the patenting option. An implication of this approach is that the estimated value should, in theory, correspond to the minimum price the patentor would be willing to accept to sell the patent.

This methodology is not exempt from limitations. Most notably, estimates do not account for innovation spillovers and/or other economic externalities. These may be significant: Schnitzer and Watzinger (2017) estimate that every USD 5m to 50m invested in US-based start-ups during 1979–1999 indirectly led to one additional innovation produced as spillover effect. Secondly, the approach implicitly assumes all non-exercised patent *options* to bear zero or negative value, even if the underlying IPs hold positive value. As such, not only the scope of the analysis must be limited to patent-holding start-ups, but also against these the methodology may underestimate the true worth of IPs.

4.1 A model of IP protection renewal and value

This section tackles the general features of our theoretical framework. For a thorough discussion of the model, the reader is referred to Appendix C. Following Deng (2007), we postulate that IV_k — innovation k's private value — is equivalent to the cumulative value of all patents within the given patent family:

$$IV_k = \sum_{j=1}^{J} PV_j \tag{1}$$

where PV_j is the value of patent j. We define PV_j as the sum of all returns accruing to the patent holder, minus the patent enforcement costs, *i.e.* renewal costs. Renewal costs can be expressed as $c(t_i) = \{c_{t_i}\}$, a sequence of non-decreasing renewal fees payable at each period t_i, $i = 0, 1, \dots, T$, where T is the maximum renewal period and t_T is typically 20 years. For simplicity, we assume renewal fees to be due precisely at the start of each period, while late payments are not foreseen. Renewal fees and renewal periods can significantly differ across countries. Within each country, renewal fee prices are often indexed to *e.g.* GDP prices, consumer prices. As such, they are updated periodically.

Following Pakes and Schankerman (1984), we impose a functional form for the return distribution. The patent revenue stream is defined by an *initial return* r_0, associated to the initial "quality" of the innovation. For instance, consider a major technological breakthrough that confers a high competitive edge to the innovator: *ceteris paribus*, s/he will be able to reap higher benefits from such innovation. In addition, we assume that revenues are subject to the exponential decay rate δ. This may be explained by technological obsolescence and/or increased pressure from competitors, who may catch-up through similar innovations falling outside the remit of the original IP claim. Thus, the return function $r(t)$ can be expressed as follows:

$$r(t) = r_0 e^{-\delta t} \tag{2}$$

At first, the assumption of such a specific functional form for patent returns may seem unwarranted. Indeed, it is not rarely that patentors apply for patent protection despite lacking a thorough strategy for the commercialisation of their IP. Nevertheless, this limitation does not appear to significantly affect estimation results: both Pakes (1986) and Lanjouw (1998) note that even when accounting for uncertainty and the discovery of new ways to commercially exploit patented IPs, no "learning" windfall can be observed by the 7th year after application.

Assuming that patentors are endowed with perfect rationality and information, the decision to renew at time t_i is only justified if the returns accruing in $[t_i, t_{i+1}]$ at least match the renewal costs c_{t_i}, *i.e.* if:

$$\int_{t_i}^{t_{i+1}} r(t)\, e^{-s\tau} d\tau \geq c_{t_i} \tag{3}$$

where s is the discount rate defining the time value of revenues.

Suppose there is no *right-censoring* of renewal rates, *i.e.* that the last observed payment can only indicate the patentor's unwillingness to withstand further renewal costs — as opposed to *e.g.*, not yet accrued renewal fees. Denote the last paid renewal period with $\lambda \in [0, T]$. As per (3), it ensues that patent revenues in $[t_\lambda, t_{\lambda+1}]$ must be greater or equal to renewal costs c_{t_λ}, while returns in $[t_{\lambda+1}, t_{\lambda+2}]$ must be lower than $c_{t_{\lambda+1}}$.

Similarly, the total (discounted) revenue stream PR, *i.e.* the value of all returns accruing in $[t_0, t_{\lambda+1}]$, can be shown to lie between:

$$z_{t_\lambda} c_{t_\lambda} \leq PR < z_{t_{\lambda+1}} c_{t_{\lambda+1}} \tag{4}$$

where $z_{t_{\lambda+m}}$ is a function of δ, $t_{\lambda+m}, t_{\lambda+(m+1)}$ and s. Discount rate s is assumed at 10% per annum as in Bessen (2008) and most similar works.[17]

To estimate the remaining quantities, we impose a parametric form to the distribution of PR. Ruling out the hypothesis that values are distributed *normally* (as per the existing literature and the claims made in the foreword of this chapter), we turn to the assumption that PR is *log-normally* distributed,[18] *i.e.* that:

$$\ln\left(PR_j\right) \sim N\left(\mathbf{x}_j \beta, \sigma_\varepsilon\right) \tag{5}$$

where $\mathbf{x}_j$ is a vector of patent characteristics. As previously mentioned, $\ln\left(PR_j\right)$ is a *latent*, unobservable variable for patent j. However, we can exploit its *observable* last renewal period $\lambda_j \in [0, T]$

[17] The model's sensitivity to this assumption is tested by varying s in the range of 5% to 15%. Because of the model's parametric form, all original MLE estimates are maintained, save for δ which shifts accordingly to counteract the increase or decrease in s. For additional robustness, we tested a firm-specific discount rate s, leveraging on firms' weighted average cost of capital (based on the methodology of Lünnemann and Mathä, 2002). Results are very similar to the ones reported in the remainder of the paper.

[18] See Bessen (2008) for an overview of the literature on patent value distributions.

to make inference about $\ln(\mathrm{PR}_j)$. The quantity λ_j is referred to as an *ordered response*, such that:

$$
\begin{aligned}
\lambda_j &= 0 \quad \text{if } \ln(\mathrm{PR}_j) < \ln(z_{t_1}c_{t_1}) \\
\lambda_j &= 1 \quad \text{if } \ln(z_{t_1}c_{t_1}) \leq \ln(\mathrm{PR}_j) < \ln(z_{t_2}c_{t_2}) \\
\lambda_j &= 2 \quad \text{if } \ln(z_{t_2}c_{t_2}) \leq \ln(\mathrm{PR}_j) < \ln(z_{t_3}c_{t_3}) \\
&\vdots \\
\lambda_j &= T \quad \text{if } \ln(\mathrm{PR}_j) \geq \ln(z_{t_T}c_{t_T})
\end{aligned}
\tag{6}
$$

Given this formulation, it is now possible to estimate β, σ_ε and δ via maximum likelihood (ML) methods. However, we must first address the additional complication — stemming from the use of recent patent vintages — that generates *right-censoring* for patents whose renewal window has yet to conclude. To address this issue we follow Gupeng and Xiangdong (2012) and introduce the *censoring variable* η_j, which has value 1 if the patent renewal window is right-censored, and 0 otherwise. For instance, the response $\lambda_j = 2$ in (6) is updated as follows:

$$
\begin{aligned}
\ln(z_{t_2}c_{t_2}) \leq \ln(\mathrm{PR}_j) < \ln(z_{t_3}c_{t_3}) \quad &\text{if } \eta_j = 0 \\
\ln(z_{t_2}c_{t_2}) \leq \ln(\mathrm{PR}_j) \quad &\text{if } \eta_j = 1
\end{aligned}
\tag{7}
$$

i.e. the revenue stream PR_j for the *active* patent j has a lower bound but no upper bound, since we cannot observe future renewal decisions.

Concluding our analysis, we compute the expected values for $\ln(\mathrm{PR}_j)$, conditional on the observed last renewal period λ_j, using ML estimates of β, σ_ε and δ. Finally, we use (1) to compute IV_k.

4.2 Renewal data

Renewal fees are due for each patent application submitted by the patentor. Against this background, our initial sample comprises 80,581 patent applications associated to the 14,292 innovations and 2,359 start-ups supported by EIF in the 1996-2012 period, as described in sections 2 and 3.

We sourced patent renewal data from databases of national and international patent offices, all accessible online. Since our original dataset contains more than 80 different patent offices (POs), we restricted our analysis to European and US patent offices, selecting first the ten most frequent offices. To improve the geographical representativeness, we further collected data for five European offices.[19] The inclusion of US renewal data follows the empirical finding that a sizeable share of EIF-backed start-ups favours the US Patent and Trademark Office (USPTO) over its European counterparts in the submission of their first IP protection claim, often abstaining from further pursuing IP protection in Europe.[20] This occurs with much lower frequency in the case of other international patent offices.

[19] The trade-off against full coverage was a need of PO-specific routines to scrape and/or bulk obtain data.

[20] We find over 7% of patenting ICT start-ups consistently following this route, while in other sectors the incidence is lower than 1%. Nevertheless, 37% of patentors adopted such practice for at least one innovation.

This geographic limitation slightly alters the notion of innovation's private value we introduced in section 4.1, restricting it to the value generated in Europe and US, the two biggest patenting markets as described in section 3.3. The 15 POs covered in the analysis make up for 93% of all patent applications submitted in these markets and amount to 55,961 application documents. In subsequent steps, we further limit our scope to applications submitted in the 1987-2012 period.[21] We obtain a final sample of 33,905 patent applications matched with renewal fee information. Table 6 lists the general features of the final dataset and compares renewal rates among different subgroups.

Based on the information contained in the final sample, we identify three key application groups:

a) EP/EP-PCT applications, which include European Patent Office (EPO) applications or Patent Cooperation Treaty (PCT) applications — submitted to the World Intellectual Property Organization, (WIPO) — further processed by the EPO. This group includes all applications related to the *national phase* of EP/EP-PCT applications. For an overview of the various patent application systems, see Chapter 3 of OECD (2009).

b) USPTO applications, which include only applications submitted to the US Patent and Trademark Office, either via PCT or directly to the USPTO.

c) (European) National applications, which include both PCT and non-PCT applications submitted directly to national European patent offices.

Patent applications to the EPO follow a more articulated path than national and USPTO patents. Yet, the EPO significantly reduces the burden (and cost) of multi-country patenting within member states of the European Patent Convention (EPC). For a complete overview of the EPO application process, see Harhoff and Wagner (2009). For the purpose of this analysis, it will suffice to mention that EP applications are first submitted to the EPO, where a first examination is carried. At the application stage the patentor typically submits a list of member countries where s/he intends to later employ the patent. At this stage and until the patent is granted, the patentor must pay renewal fees to the EPO. If the EP patent is granted, it enters the so-called *national phase*. Here, in order to maintain the IP protection in the previously elicited countries, the patentor has to pay each national office separately.

Renewal fees are sourced from the websites of EPO, USPTO, WIPO and PatentVista. Historical data on renewal fee prices are available for EPO applications since 1978 and for USPTO since 1997. We convert all amounts EUR/ECU using end-year historical exchange rates published by the ECB.

With regards to fee prices for other national POs, we were not able to retrieve historical fee schedules. As a second-best solution, we retrieved the latest observable schedule (typically 2015/16) from the above-mentioned sources and assumed historical prices to correspond to current fee prices in real terms. The assumption is based on the observation of Pakes *et al.* that *"in most countries we have studied there has not been much intertemporal variation in these [fee] schedules in real terms"* (Pakes *et al.*, 1989, p. 369). It should be noted, however, that Pakes *et al.* refer in particular to short-term variation. Hence, we expect some bias with regards to older application vintages, due to our

[21] The upper bound restriction is due to renewal data being collected up until 31/12/2016. As such, most applications submitted after 2012 will not have witnessed enough time for the accrual of renewal fees.

Table 6: Sample summary statistics and patent renewal rates

	Percent renewed until or expired during:					Observations
	1st–4th year	5th–8th year	9th–12th year	13th–19th year	full term	
All patents	25.15	38.27	20.88	12.84	2.86	33,905
Application status						
Active	38.67	32.09	18.02	7.05	4.16	21,082
Lapsed	2.91	48.43	25.57	22.37	0.73	12,823
Application group						
EP/EP-PCT patents (incl. national phase)	18.46	37.03	24.78	18.42	1.31	21,303
USPTO patents	47.09	33.01	12.81	–[a]	7.10	9,400
National patents	5.22	61.96	18.64	13.46	0.72	3,202
Country of Patent Office						
EP	32.16	44.69	18.63	4.51	0.02	11,453
US	47.09	33.01	12.81	–[a]	7.10	9,400
DE	6.05	25.59	27.80	37.39	3.17	4,162
GB	–[a]	71.13	17.38	11.13	0.35	2,255
AT	–[a]	54.48	27.05	16.28	2.19	1,874
ES	0.68	18.81	39.83	37.85	2.83	1,765
FR	22.83	43.15	22.20	11.02	0.79	635
Other POs[b]	0.34	19.44	35.62	41.89	2.71	2,361
Start-up macro-region						
BI	22.18	45.19	19.26	11.71	1.66	9,834
DACH	25.03	36.97	21.10	14.21	2.68	8,049
FR&BENELUX	25.17	35.90	22.07	14.32	2.53	7,869
ROW	31.83	34.07	20.34	8.59	5.16	4,822
NORDICS	24.60	31.53	23.85	15.71	4.30	2,813
SOUTH/CESEE	23.83	38.48	18.75	14.84	4.10	512
Technology field						
Life sciences	25.70	35.76	21.38	14.42	2.73	16,528
ICT	24.82	40.83	20.29	11.25	2.81	8,018
Electronics	24.41	41.69	19.05	11.60	3.24	5,248
Other/Missing	24.50	39.02	22.33	11.19	2.97	4,111

[a] No renewal fees due in the period; [b] DK (obs: 894), PT (628), FI (56), SE (21), HR (11), PL (11), NL (7), BE (6).

analysis' longer-run perspective.[22] In the final step, all monetary amounts related to fee prices are converted to EUR, deflated by national GDP deflators and expressed in 2005 prices.

To estimate $\ln(\mathrm{PR_j})$, we identify a number of value predictors drawing from the existing literature. The goal is to select characteristics related to the quality of the underlying innovation. For instance, a higher *patent stock*, *i.e.* the size of the firm's patent portfolio when patent j was submitted, has shown an inverse relationship with patent value (Bessen, 2008), confirming the findings in Lanjouw and Schankerman (2004) that patent productivity is inversely related to patent value and, to some extent, the "invention potential exhaustion" hypothesis in Evenson (1991). Similarly, a number of studies point to the positive relation between the inventor team size and the value of the innovation (*e.g.*, Wuchty *et al.*, 2007).

In addition, we account for a series of more conventional predictors of patent value, *e.g.* citations and the number of claims in the patent. These quantities have been previously employed as proxies of patent value (Trajtenberg, 1990). In the case of citations, we must differentiate between citations *made*, so-called *reverse citations*, and citations *received* (*forward citations*). Moreover, *reverse cita-*

[22] For instance, March 19 2013 witnessed the largest price increase in USPTO renewal fees. Prices increased from a minimum of 24%, up to a 54% raise for the third and last renewal instalment.

tions directed at non-patent literature (*e.g.* scientific papers, reports) have been shown to affect the generality and *appropriability* of the underlying innovation (Trajtenberg *et al.*, 1997).

With regards to patent claims, we first consider crude measures such as the total number of claims. In addition, we exploit data on claims to derive proxies of patent's technical content. In particular, we choose the *median claim length-to-words ratio*, which computes the average length of words among claims of a specific patent, then draws its median value.[23] We hypothesise that a higher incidence of technical terms will produce a higher median claim length-to-words ratio, and we seek to measure how this feature relates to patent value. Table 7 lists descriptive statistics for the explanatory variables.

Table 7: Summary statistics of explanatory variables

	Obs.	Mean	Std. Error	Min	Max
Patent stock	33,905	21.94	33.165	0	256
Number of inventors	33,905	5.37	5.515	1	60
Citations made	33,905	14.41	30.921	0	999
Citations received	33,905	4.79	20.588	0	1,797
Non-patent citations made	33,905	7.63	20.773	0	579
Median claim length-to-words ratio	33,905	6.26	0.556	5.26	8.57
Patent received no citations†	33,905	0.28	0.449	0	1
Patent made no citations†	33,905	0.64	0.481	0	1
Patent made no non-patent citation†	33,905	0.42	0.494	0	1
Application period:					
1987-2001†	33,905	0.24	0.425	0	1
2002-2007†	33,905	0.51	0.500	0	1
2008-2012†	33,905	0.25	0.436	0	1
Technology field:					
ICT†	33,905	0.24	0.425	0	1
Electronics†	33,905	0.15	0.362	0	1
Life sciences†	33,905	0.49	0.500	0	1
Other†	33,905	0.12	0.326	0	1
Start-up macro-region:					
DACH†	33,905	0.24	0.425	0	1
NORDICS†	33,905	0.08	0.276	0	1
FR&BENELUX†	33,905	0.23	0.422	0	1
SOUTH†	33,905	0.02	0.123	0	1
BI†	33,905	0.29	0.454	0	1
ROW†	33,905	0.14	0.349	0	1

† dichotomic variable

4.3 Empirical results

4.3.1 Patent value by estimation group

Table 8 illustrates the estimation results. Due to significant differences in renewal fee schedules among various application groups, we were unable to fit the entire sample to the model at hand. As such, we carried out a separate analysis for each estimation group introduced in section 4.2.

Column (1) of Table 8 contains the coefficients of the regression on the EP/PCT subsample of patent applications. We account for the EP *national phase* by assigning the *censored* status, *i.e.* $\eta_j = 1$, to granted EP applications entering this stage. We motivate this choice by observing that, after grant

[23] To avoid the difference in average word length be driven by different patent languages, we only calculate this index for main/equivalent patents written in English.

Table 8: Maximum likelihood estimates of the patent renewal model.

	EPO & national phase patents (1)	National patents (2)	USPTO patents (3)	USPTO patents with $\delta = 0.25$ (4)
	MLE	MLE	MLE	MLE
$\ln$ (Patent stock)	-0.2963***	-0.0657	-0.2756***	-0.0850**
	(0.030)	(0.084)	(0.090)	(0.042)
$\ln$ (Number of inventors)	0.3966***	0.0004	-0.2416*	-0.1080*
	(0.045)	(0.140)	(0.136)	(0.065)
$\ln$ (Citations made)	1.5079***	0.8295**	0.8754***	0.4504***
	(0.108)	(0.345)	(0.184)	(0.081)
$\ln$ (Citations received)	0.6141***	0.4612***	1.5594***	0.7373***
	(0.045)	(0.136)	(0.186)	(0.052)
$\ln$ (Non-patent citations made)	-0.5637***	-0.8838**	-0.2007	-0.1004
	(0.107)	(0.408)	(0.183)	(0.089)
$\ln$ (Number of claims)	-0.2228***	-0.1609	-0.7772***	-0.3718***
	(0.051)	(0.155)	(0.173)	(0.076)
Median claim length-to-words ratio	-0.1349**	0.6547**	-0.8503***	-0.4274***
	(0.065)	(0.254)	(0.209)	(0.094)
Patent made no citation†	1.9742***	-0.4231	-4.2608***	-2.0226***
	(0.199)	(0.678)	(0.884)	(0.378)
Patent received no citation†	0.9685***	0.6404**	0.0997	0.0501
	(0.113)	(0.313)	(0.422)	(0.207)
Patent made no non-patent citation†	0.9281***	-2.1247***	0.1874	0.1025
	(0.163)	(0.645)	(0.502)	(0.244)
Constant	8.6020***	5.1791***	16.2873***	10.9265***
	(0.520)	(1.704)	(1.780)	(0.697)
Application period[a]	Yes	Yes	Yes	Yes
Technology field[b]	Yes	Yes	Yes	Yes
Start-up macro-region[c]	Yes	Yes	Yes	Yes
δ	0.251	0.041	0.849	0.251
σ_ε	3.07	4.02	7.59	3.72
Median expected revenue (2005 EUR)	107,044	931	171,221	6,361
Mean expected revenue (2005 EUR)	1,079,053	66,880	2,980,000,000	228,853
Log-likelihood	-35402	-4391	-8605	-8640
N° of observations	21,303	3,202	9,400	9,400

* $p<0.05$, ** $p<0.01$, *** $p<0.001$; † dichotomic variable;
[a] Application periods: *1987-2001* (baseline), *2002-2007*, *2008-2012*. For columns (3) to (4), dummy "post-2008" used instead; [b] Technology fields: *ICT* (baseline), *electronics*, *life sciences*, *others*; [c] For the composition of regions refer to footnote 12; family cluster-robust standard errors in brackets.

date, the patentor is relieved from the duty to pay renewal fees to the EPO. At the same time, s/he can keep the patent enforcement through payments directed at each national office. Therefore, the *value* of an EP application leading to grant can be interpreted as right-censored.

The sample of EP/PCT applications yields a rate of technological decay $\delta = 0.25$, higher than in Bessen (2008) and in general lying in the upper range of decay rate values estimated in the literature. We believe this is due to the nature of our sample of patentors, composed exclusively of new ventures. Indeed, when estimating the model parameters on a subset of smaller firms, Bessen also encounters a higher value for the technology decay rate. Similarly, we note from Gupeng and Xiangdong (2012) that our correction to account for *censored* applications tends to further inflate the value of δ.

Column (2) shows the results of the regression on the national patents' subset. Compared to the former group, these patents present a much lower rate of technological decay ($\delta = 0.04$) as well as lower median (EUR 931, in 2005 prices) and average expected returns. With respect to the lower value of δ, we can observe a number of potential drivers of such significant difference, *e.g.* a higher proportion of ICT-driven innovations, and a lower proportion of seed stage, potentially more *disruptive* companies. However, the most plausible explanation would be twofold: first, innovators may have a better grasp of the appropriable returns from a patent when pursuing national IP protection, compared to the case of an international, European-wide patent. Second, the data hints to a *selection effect*, justified by the lower rate of purely national applications, [24] causing firms to pursue national patents especially in the case of moderate (but predictable) returns from innovation.

Ultimately, this finding leads to a potential limitation of our simplified model, one that concerns the theorised constant nature of the decay rate δ. This point is also raised by Bessen in the context of USPTO patent applications submitted by foreign firms. Our regression on the USPTO subset of patents, shown in Column (3) of Table 8, further reinforces this view. For this group, we estimate δ =0.85, more than three times the rate observed in the EP/PCT group of patent applications. Like in Bessen (2008), we note that such higher δ is accompanied by a significant increase in the standard deviation σ_ε. Bessen argues that such high δ is evidence of the failure of our constant depreciation assumption. We adhere to this view and, following his recommendation, Column (4) re-estimates the model by constraining the coefficient of δ to 0.25, *i.e.* the estimated value for the EP/PCT sample.

4.3.2 Patent value and patent characteristics

Despite our regressions' foremost purpose to consistently predict patent values, numerous insights also stem from the analysis of the explanatory variables. On this point, we should note that the models portrayed in Table 8 include predictors consistently emerging as significant, though numerous alternative specifications have been tested and yielded no significantly higher predictive power. In addition, all models in Table 8 include a series of innovation- and startup-level controls, such as the application period, the technology field (see Appendix A) and the start-up's geographical region.

Our estimated coefficients are mostly in line with the existing literature, albeit with some noteworthy exceptions. First, our data confirms the negative relationship between a patent's value and the *patent stock*, consistent with prior studies highlighting a decrease in patent productivity as businesses become more mature. Second, we find that the inventor team size positively relates to the patent value — in line with Wuchty *et al.* (2007).

The relationship between patent value and citation data is more erratic. With regards to citations made by EIF-backed patentors, we find these to be positively related to patent value in all estimated subsets. Due to a significant share of patent applications making no citation, we hypothesise the presence of a structural break in such correlation. We thus introduce one additional binary regressor that takes value 1 if the patent does not provide any citation to prior IP. This binary variable has a negative coefficient for USPTO — as expected — but positive for EP/PCT. This latter finding, at first counter-intuitive, may be due to the fact that citations in EP/PCT patents are provided by the EPO

[24] However, note that PCT applications never requiring the involvement of the EPO are also in this subset.

itself, and while applicants can still submit further references, it would not be granted for *reverse citations* in EPO patents to positively affect patent value. In fact, in such setting a lack of prior art may actually be indicative of a particularly original innovation (*i.e.* a breakthrough technology).

Results on *forward citations* (*i.e.* citations received) show that for all patent subsets receiving more (less) citations is related to higher (lower) patent value. However, in the EP/PCT and national subsets we also find the binary coefficient to be significant and positive, leading to the following interpretation: on the one hand, a higher number of forward citations is beneficial to patent value. On the other, patents with zero forward citations are significantly more valuable than patents with at least one such citation. Overall, evidence on the ambiguous role of forward citations is widespread in patent value research. Maurseth (2005) provides further proof and discussion.

Turning to patent claims, we find that a higher number of these is negatively related to patent duration, and therefore its value. This finding is in sharp contrast with previous studies (*e.g.* Bessen, 2008; Lanjouw and Schankerman, 2004; Barney, 2002), so we speculate that it may be linked to the peculiar patenting behaviour of start-ups. According to van Zeebroeck (2009), in the presence of business and technological uncertainty, it may be convenient for firms to *"delay grant decisions on their patent applications to a certain point when placed in particular business or technological conditions"* (*ibid*, p.6). This typically translates into very broad applications, containing a large number of claims. However, this choice may prove detrimental for start-ups, since pending patents may contribute to the overall business uncertainty and discourage follow-up investors. We find limited evidence of this by noting the negative relationship between grant rates and the number of claims.

Further contributing to this narrative, we find that the *median claim length-to-words ratio*, used to highlight the technical depth of a patent, is also negatively correlated with patent duration, save for the smaller subset of national patents. Furthermore, contrary to Barney (2002) none of our model specifications finds the word length of claims to be a significant predictor of patent value. Overall, we conclude that in the case of young innovative start-ups the pursuit of IP protection via narrowly defined patents, making limited use of technical terms, is linked to higher patent duration as well as higher returns from IP.

4.4 Analysis

4.4.1 Comparison to other studies

We obtain patent values by deducting actualised renewal costs from each expected patent revenue. Detailed information on the resulting patent value distributions is provided in Appendix D. Table 9 compares our results with a number of prior studies to assess the accuracy of the former. Table 9 also includes results from Gambardella *et al.* (2008) who adopt a survey-based approach to elicit patent value — as opposed to all other studies based on Schankerman and Pakes's model. The results of this work are helpful to assess the size of the downward bias that theory predicts with respect to estimates based on patent renewal data.

Table 9 indicates that our value estimates are in line with the relevant literature, while at the same time we note how a crude comparison of median and mean estimates reveals a significantly higher skewness of our results (further details on this are provided in Appendix E).

Table 9: Comparison of estimated patent values

Study	Patentees	Granted only	Patent cohort	Patent Office	Patent Value ('05 EUR): Median	Mean	δ
Pakes (1986)	All	No	1951-'79	FR	929	9,797	0.17
Pakes (1986)	All	No	1950-'74	GB	3,234	15,682	0.21
Pakes (1986)	All	Yes	1952-'72	DE	7,887	20,394	0.12
Schankerman and Pakes (1986)	All	No	1951-'79	FR	1,474	11,580	0.10
Schankerman and Pakes (1986)	All	No	1950-'76	GB	3,967	14,842	0.18
Schankerman and Pakes (1986)	All	Yes	1952-'78	DE	10,118	31,883	0.12
Lanjouw (1998)	All	Yes	1953-'80	DE	12,945	22,161	0.05
Koléda (2005)	All	No	1951-'93	FR	3,291	13,092	0.08
Serrano (2005)	All	Yes	1983-'02	US	23,485	73,063	0.27
Deng (2007)	All	No	1978-'96	EPO	34,420	823,702	0.15
Bessen (2008)	All	Yes	1991	US	7,768	84,628	0.14
Bessen (2008)	Foreign cos.	Yes	1991	US	67,478	3,145,907	0.27
Bessen (2008)	Foreign cos.	Yes	1991	US	17,779	116,824	0.15†
Bessen (2008)	Listed cos.	Yes	1985-'91	US	53,372	98,291	0.13
Bessen (2008)	Non-listed cos.	Yes	1991	US	20,793	223,334	0.16
Grönqvist (2009)	All	No	1971-'90	FI	1,682	7,013	0.09
Gupeng and Xiangdong (2012)	All	Yes	1985-'09	CN	1,808	24,602	0.34
Gambardella *et al.* (2008)‡	All	Yes	1993-'97	EPO	379,368*	3,554,409*	n.a.
This working paper	VC start-ups	No	1987-'12	–§	796	66,459	0.04
This working paper	VC start-ups	No	1987-'12	EPO	105,612	1,072,812	0.25
This working paper	VC start-ups	No	1987-'12	US	5,868	227,622	0.25†

† δ coefficient constrained; ‡ Based on survey data; * Gross of renewal fees; § PO codes in Table 6.

4.4.2 The value of innovations for EIF-backed startups

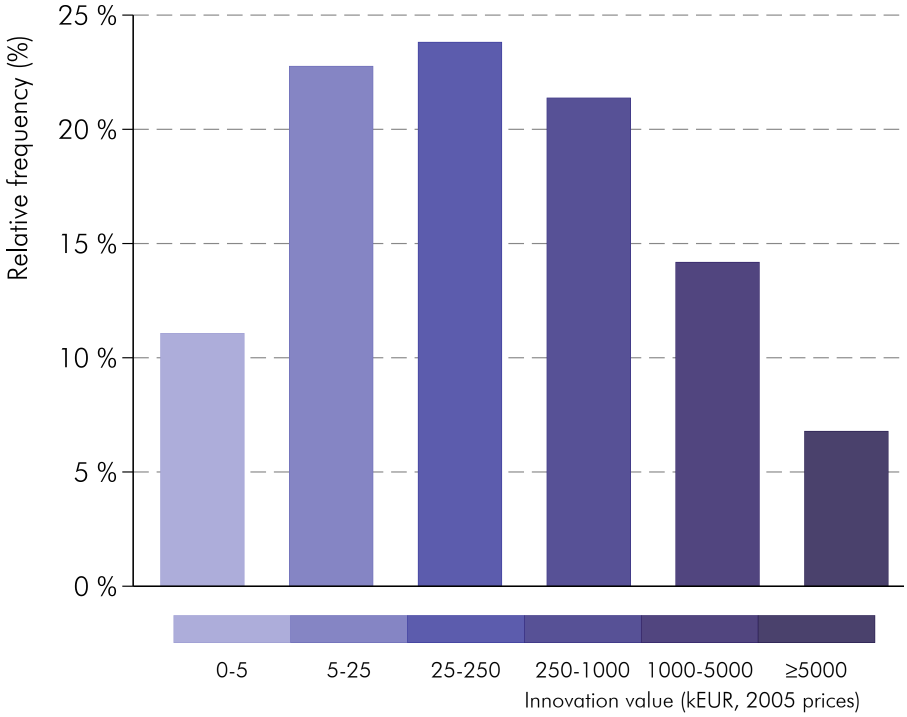
Based on the patent value estimates discussed in the previous section, we now turn to the analysis of the economic value of start-up innovations. As discussed in section 4.1, the value of a given innovation is proxied by the aggregate value of patents in the related patent family. We estimate the economic value for 11,597 unique patent families associated to start-ups supported by the EIF. Expressed in 2005 prices, values range from a few hundred Euro to more than EUR 402m, with a median and average price of EUR 138k and EUR 2.2m respectively. As expected, the distribution of innovation values is heavily skewed. For instance, we find that only 96 innovations hold a value of EUR 50m or higher. These high-valued innovations are associated to 66 start-ups, out of a total 984 start-ups in our sample with at least one patented innovation. Figure 11 provides further insights on the distribution of values for the entire sample of innovations.

Sectoral differences

Figure 11 can be used as a basis to compare innovation values across different subsets of our sample.[25] On this premise, Figure 12 compares the distribution of innovation values among the two foremost industries, *i.e.* Information and Communication Technology (ICT) and Life sciences. Figure 12 reveals fundamental differences not only in the innovative capacity of start-ups operating in these two sectors, but also signals opposing IP protection strategies among the two groups. To

[25] We limit our discussion here to the most significant findings. For additional information on all relevant sample subsets, see Appendix F.

Figure 11: Histogram of innovation values



Note: based on a sample of 11,597 innovations from 984 EIF-backed startups with complete value data.

support this claim, we note how the distribution of values for ICT start-ups peaks in the EUR 25k – 250k value range and is moderately less skewed than in the case of life sciences, which have their innovation distribution peak earlier in the EUR 5k – 25k bracket. A possible interpretation of this difference lies in the fact that innovations in life sciences may be subject to lower entry barriers for IP enforcement, *e.g.* due to a lower chance of imitation from competitors prior to the proven success in clinical trials. Against this background, the distribution of ICT innovations may suffer from *selection bias*, causing less promising inventions to be excluded *a priori* from patenting.[26] At the same time, the high incidence of outliers in life science innovations is cause for their higher overall worth.

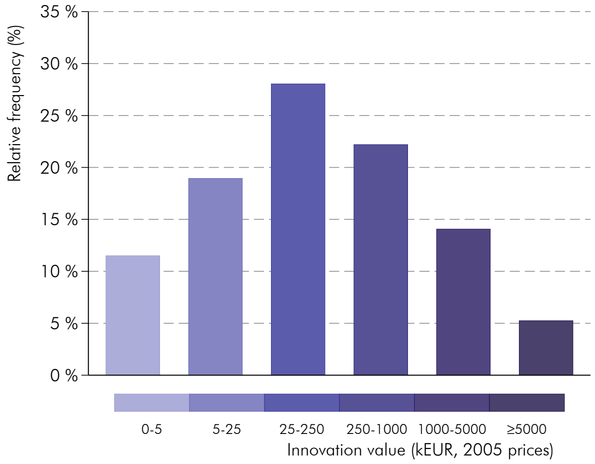
To shed further light on this topic, Figure 13 displays the distribution of innovation values across the twenty most frequent technology fields discussed in section 3.2. Figure 13 ranks innovation fields from highest to lowest in terms of the median, providing evidence in support of our prior hypothesis: life sciences core fields such as oncology, metabolic disorders and infectious diseases treatments all show the highest average values, but occupy the lowest tier of the median ranking. Conversely, fields related to ICT and electronics typically hold the foremost positions and show less dispersed interquartile ranges. Interestingly — and perhaps fortuitous — the field of medtech, combining discoveries in life sciences and ICT/Electronics, lies almost precisely between its parent categories.

Geographical differences

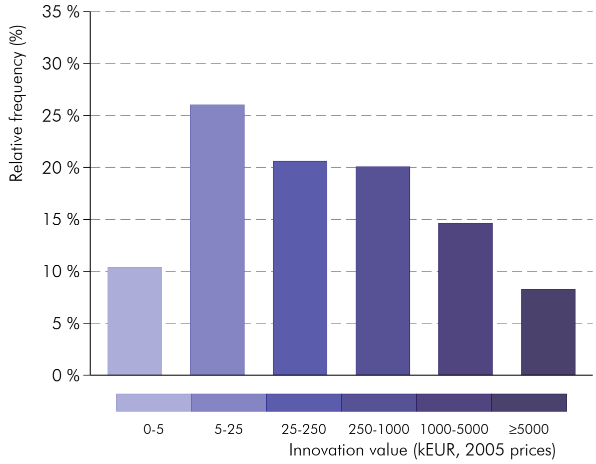
Figure 14 hints that a similar phenomenon may be occurring at the geographical level. Figure 14a illustrates the distribution of innovation values for start-ups based in the British Isles. As discussed in

[26] This phenomenon may not only be limited to innovations lacking the potential to produce outstanding economic returns, but also covers IPs whose revenues may be harder to protect, easier to imitate, *etc.*

Figure 12: Innovation values by start-up sector



(a) ICT

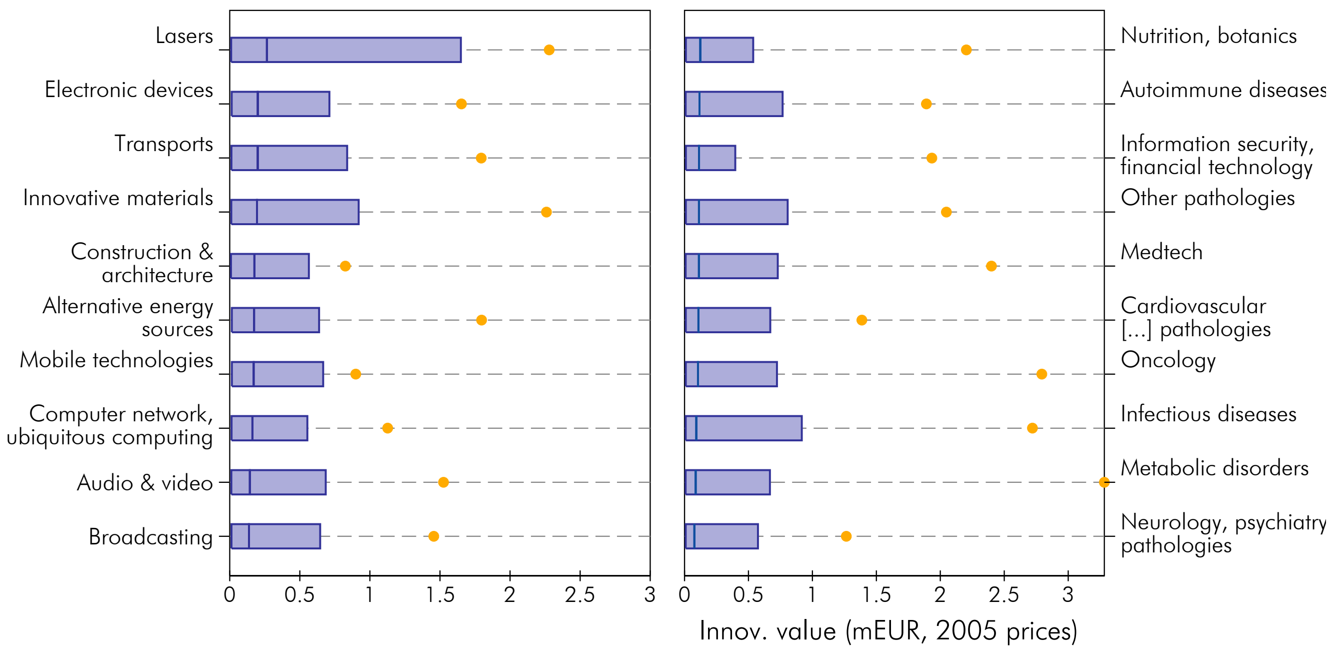


(b) Life sciences

section 3.3, this group produced the highest amount of innovations in the observed period. However, the value of these innovations is lower compared to start-ups in other European regions. This is proven by the higher-valued ranges in Figure 14a being consistently less frequent than in Figure 11.

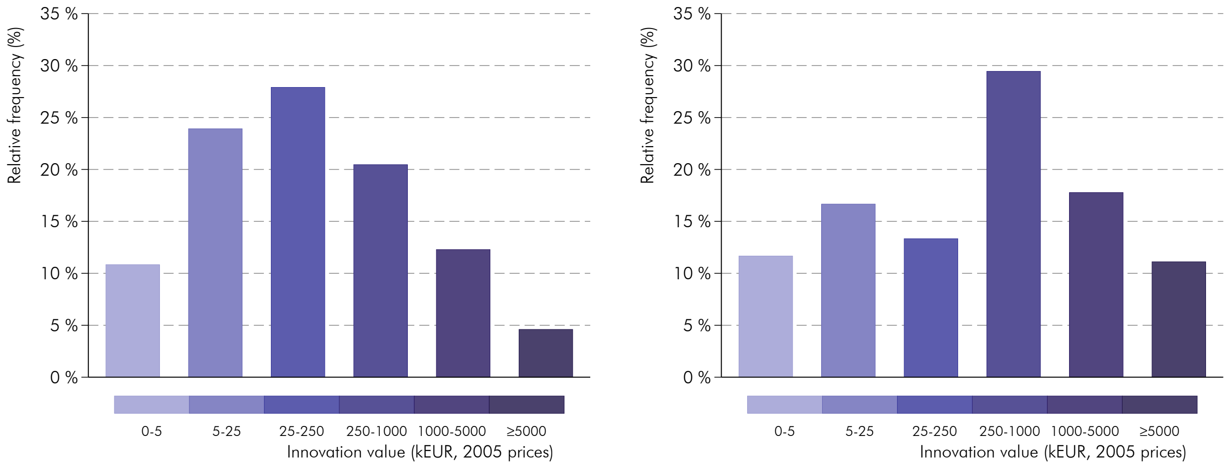
At the other end of the spectrum, Figure 14b hints that, despite start-ups in the Southern European/CESEE regions being generally less productive in terms of patented innovations, their output has on average a higher value than in competing macro-regions. While we should refrain from assigning conclusive evidence to this finding — due to the relatively small size of the Southern European/CESEE innovation subset — Figure 14b hints that selection bias may be affecting the shape

Figure 13: Mean, median and interquartile range of patent families by innovation field



Note: based on a sample of 8,657 innovations associated to 894 EIF-backed startups. Blue boxes represent the interquartile range. The vertical blue line intersecting each box represents the median, while the yellow dot represents the mean.

Figure 14: Innovation values by start-up macro-region



(a) British Isles

(b) Southern Europe and CESEE

of the distribution in this group. In this case, institutional limitations (*e.g.* perceived costs and length of litigation procedures) may be deterring start-ups from pursuing IP protection via patenting (see also OECD, 2011). Supporting evidence is provided by Eurostat's Community Innovation Survey (CIS): Peneder (2010a) reports comparatively limited use of patents and other IP rights tools (*e.g.* trademarks, copyrights) for firms in these regions. A further insight worth of mention concerns start-ups in the Nordic area, where we observe a generally higher value of start-up innovations. Nordic start-ups also tend to be less productive than the average. However, contrary to new ventures in the South/CESEE region, these rank high in terms of patent propensity, hinting at driving forces other than pure selection bias. On this point, in Appendix G we find that start-ups in Southern Europe/CESEE and the Nordics face a significantly lower data coverage rate. Although the magnitude of the bias is unlikely to affect results for South/CESEE start-ups, only further research may dissipate our reservations for the second case.

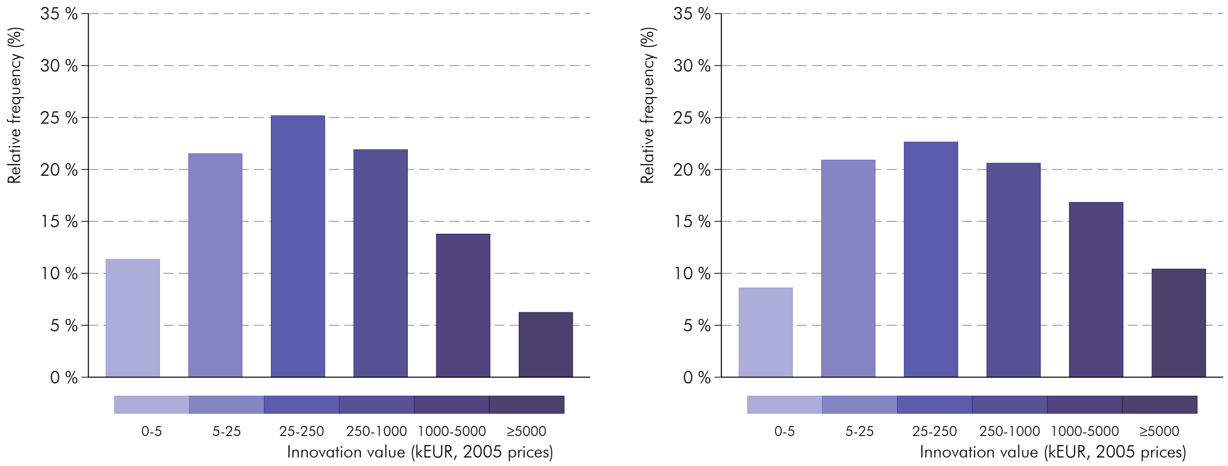
Age and timing of innovations

We conclude this section by comparing innovation values and the age of start-ups at first EIF-backed investment. The seminal work of Macmillan *et al.* (1985) raised awareness on the role of patents in the decision-making process of venture capitalists. Since then, numerous empirical works have further discussed the importance of patents in the start-ups' pursuit of external financing (see *e.g.* Hottenrott *et al.*, 2016; Coad *et al.*, 2016). In particular, Hoenen *et al.* (2014) analyse US-based biotechnology start-ups, financed in the 2001–2011 period, finding that patents were a significant predictor of first-round financing, but not second-round financing. Against this background, we would expect the pruning of low-valued IPs to be more prominent for younger start-ups.[27]

Figure 15 addresses the topic by comparing innovation values between the two groups. Indeed, Figure 15a confirms that innovations for younger start-ups are slightly skewed towards higher values. However, it is for firms in the 5 to 10 age group that we find most evidence in support of selection

[27] Unfortunately, our dataset does not track financing rounds. Thus, in the remainder we rely on the assumption that more mature start-ups face a higher likelihood of follow-on investment than younger ventures.

Figure 15: Innovation values by start-up age



(a) 0 to 2

(b) 5 to 10

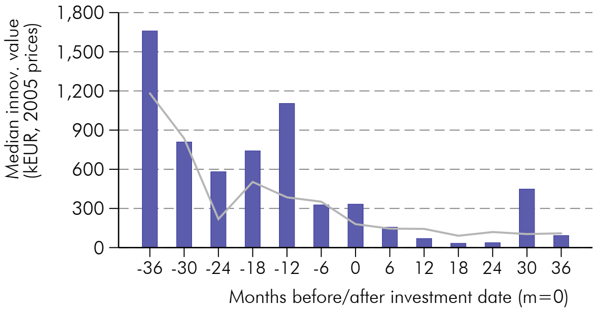
bias. We test this hypothesis by regressing the logarithm of innovation values on age, observing a positive significant correlation. However, further controlling for the time lag between the innovation's first application date and the first VC investment date, the age effect becomes mostly non-significant (results shown in Appendix H). Although we could not find conclusive evidence on the relationship between age at first VC investment and innovation value, the correlation between innovation timing and value certainly calls for further investigation. To this end, Figure 16 plots the median values of innovations for cohorts falling within 3 years of the first VC investment date.[28] For both initial (Figure 16a) and follow-on innovations (Figure 16b), values prior to investment date are unequivocally higher than in the post-investment period. As noted in section 3.5, patent ownership prior to investment is widespread among EIF-backed start-ups, with 56 percent of patentors having initiated at least one patented innovation prior to investment date.

To explain this result, we consider two different hypotheses. First, we theorise our finding to be proof of the *selection effect* of investors, who prove effective in *sorting* start-ups by their innovative capacity — provided that patent applications are available. Start-ups lacking patent production prior to investment thus tend to be assessed on different grounds, not necessarily related to their propensity to patent. The *selection function* of VC firms is often highlighted in the venture capital literature: Peneder (2010b) analyses VC- and non-VC-backed Austrian start-ups, observing a significant impact on start-up growth, but no tangible effect on innovation creation after investment. The author notes, however, that VC-backed start-ups tended to be patentors disproportionately more than their non-VC backed counterparts, pointing out the significant role of investors to "pick", rather than "make", highly innovative start-ups. Similarly, Bronzini *et al.* (2017) analyse data on Italian start-ups to find that VC-backed companies face significant growth premia in all indicators but patent propensity.

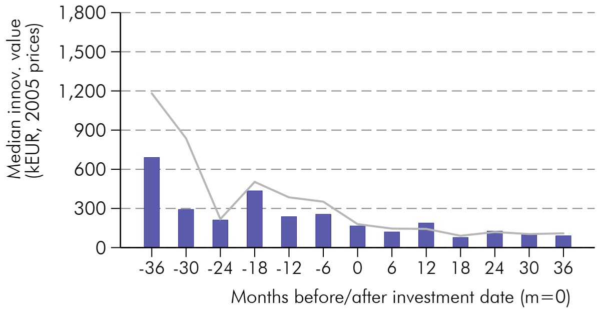
Conversely, our second hypothesis confers a significant and positive impact of VC financing on the innovative capacity of start-ups. In this scenario, start-ups receiving financial backing obtain a twofold benefit: on the one hand, they are relieved from financing constraints and this in turn could lower their barriers to patenting (see Hall *et al.* (2016); Coad *et al.* (2016) for a discussion), which may

[28] While the skewed distribution imposes the use of medians, averages lead to qualitatively similar results.

Figure 16: Median innovation value prior/following first EIF-backed investment



(a) Initial innovation



(b) Follow-on innovation

Note: only innovations three years before/after investment are shown. The grey line portrays the 6-months rolling median.

explain the lowering of median values for innovations submitted after the investment date. At the same time, managerial support from VC firms may be crucial for start-ups to accelerate their path towards commercialisation and increase potential returns from pre-existing innovations. This view is consistent with Hellmann and Puri (2000), who find that venture capital financing led Silicon Valley-based start-ups to decrease their time-to-market. At the macro level, Samila and Sorenson (2010) also highlight the role of venture capital as a catalyst for commercialisation of existing innovations. It is not possible to identify the prevailing hypothesis with the data at our disposal. Nevertheless, we point out that the existing literature — mainly focusing on the post-investment phase — may have overlooked a potentially significant channel for VC financing to affect start-ups. It is also worth noting that despite their diverging implications, the two hypotheses may not necessarily be mutually exclusive. We leave the burden of proof to further research, based on *e.g.* counterfactual assessment.

4.4.3 VC financing and the innovation multiplier effect

We conclude our assessment by discussing the relationship between VC financing and the value of supported innovations. The analysis is carried by aggregating innovation values at the level of the start-up. We find that between 1996 and 2014, EIF supported patented innovations for a total estimated volume of EUR 22.38b – 28.38b (2005 prices).[29] It ensues that the average patentor start-up generated about EUR 24m in innovation value in the same period (EUR 3m for the median).

On this premise, we turn to the estimation of the multiplicative factor linking EIF-backed VC investments and innovation value produced by start-ups. Such *multiplier* bears no virtue of causality, *i.e.* it does not provide evidence of EIF-backed financing directly impacting on the economy, particularly not at the observed scale. Nevertheless, it provides useful insights on the transmission channel between VC financing and innovative creation. Furthermore, the inverse of such multiplier can measure the *efficiency* at which start-ups are able to convert injected capital into innovative value.[30]

[29] The 95% confidence level estimate follows the smaller sample of patentors due to missing/incomplete data. Against the limitations in Appendix G, we estimate mean ranges for patentors under the *missing completely at random* assumption, on the basis that aside from geography the sample is rather representative.

[30] A key assumption is that the observable EIF-backed investment constitutes the totality of the VC financing received by the start-up. Should this not be the case, our figure will overestimate the actual efficiency ratio.

To estimate the innovation multiplier, we aggregate overall VC investment volumes supported by EIF in the same period and, similarly to patent values, we deflate nominal amounts using the GDP deflator of the start-up's nation. We thus estimate a multiplier effect of 2.74 EUR, which can be interpreted as "for every Euro of EIF-supported VC financing, start-ups have been able to generate, on average, 2.74 Euro of patented innovation". Accounting for the intermediated approach of EIF and the additional leverage channel of VC firms, we find that every Euro of VC financing provided by EIF has been transformed by start-ups, on average, into 14.95 Euro of patented innovation.

In line with our expectations, the distribution of this index is highly skewed.[31] The largest share of VC-backed start-ups are typically not efficient in transforming VC financing into patented value, since the portfolio-wide median centres around EUR 0.09 generated per Euro invested. While this is mainly driven by the larger subset of non-patentors, even among patenting companies the median multiplier is estimated below parity at approximately EUR 0.66.

Start-ups active in life sciences industries are highly likely to produce patented value (on average EUR 5.64 per Euro invested), followed by manufacturing firms and in particular those active in industrial automation (average multiplier of 3.72 for the whole industry). Start-ups operating in information and communication technology are significantly less prone to generate patented value, but still return on average EUR 1.18 per Euro invested. Conversely, the mean multiplier is below 1 in the services industry (save for consumer services, where it is slightly above parity) and green-tech. Finally, Figure 17 displays the average innovation multiplier of 183 NUTS-2 regions receiving EIF-backed investments in the 1996-2014 period. Expectedly, Figure 17 is largely representative of the geographic distribution of innovations previously portrayed in Figure 5.

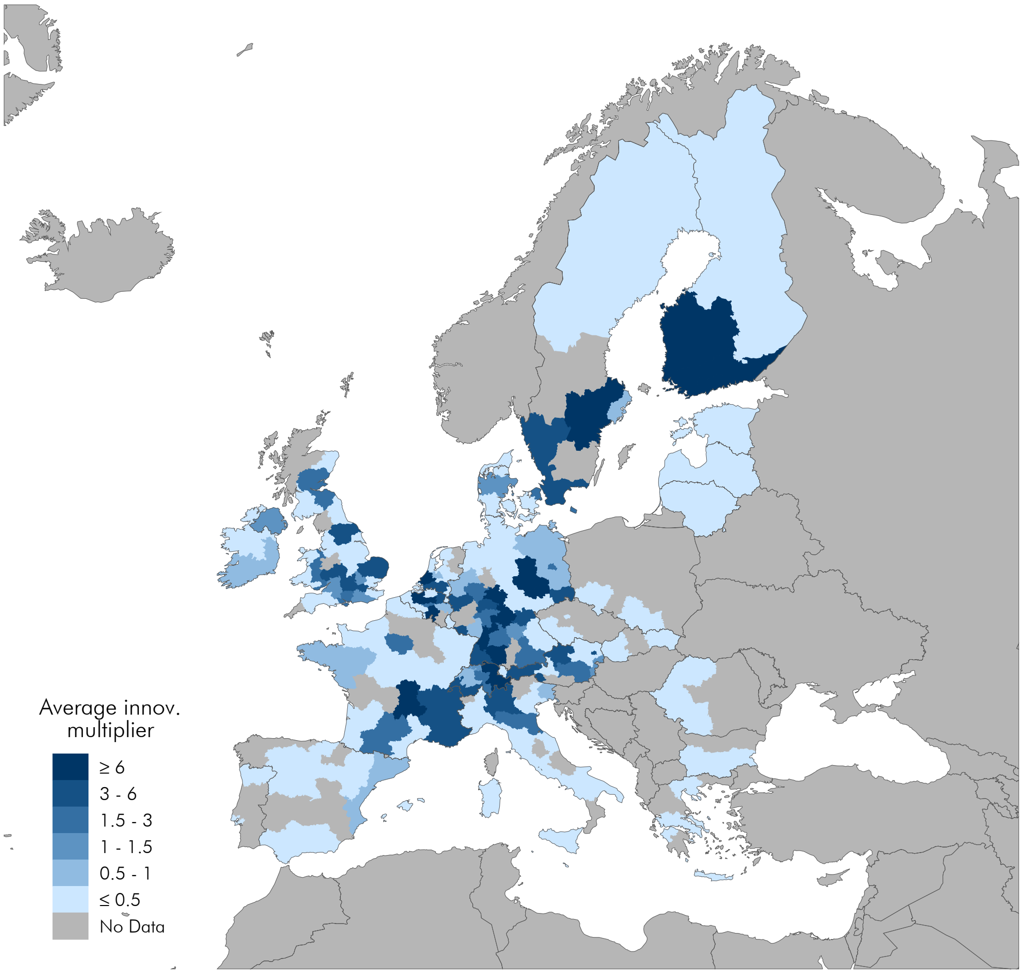
5 Conclusions

Patents are an essential element of the innovative SMEs' toolbox: they not only increase start-ups' competitive position, but also reduce information asymmetries between a start-up and potential investors and thereby act as a signalling device to attract external financing. Against this background, this paper analysed the patenting behaviour of EIF-backed VC start-ups. We highlighted the remarkable growth in EIF's patent portfolio between 1996 and 2012. First, we focused on the sectoral and spatial distribution of EIF-backed innovations and listed some of the most targeted technology fields. Second, we considered some strategic aspects of innovation, such as patents' geographical coverage. The analysis showed that start-ups seek to protect their innovation mainly on their domestic market. Coverage rates thus tend to mirror the spatial distribution of EIF-backed VC investees, with about 4 in 5 innovations protected on the European continent. Also the Americas proved to be an important market for European VC investees, reflected in a 65 percent coverage rate.

Another strategic aspect we considered concerns the timing of patent registration. This analysis revealed the existence of a dual relationship between VC and patenting activity. On the one hand, patents serve as a quality signal for VC investors, as the majority of first-registered patents of a given investee are registered before the first investment year. In this context, early innovators proved to be intense innovators, implying that age at first innovation registration could also serve as a

[31] We note one extreme outlier in the distribution: its removal induces a 10% drop in our prior estimate.

Figure 17: Average innovation multiplier by NUTS-2 region



Note: based on a sample of 2,121 start-ups supported by EIF with data on innovation value and geographic location.

useful indication to innovation-minded investors, signalling high future patent activity. On the other hand, the statistics revealed that the vast majority of overall innovations were registered *following* the first investment year. This provides evidence of a reverse relationship between VC funding and innovation as it indicates that VC funding enables start-ups to continue innovating and patenting their inventions once funding has been made available. We also noted how inventor teams behind EIF-backed innovations have grown increasingly international. However, female participation in patented research remains generally low, despite significant field-level differences.

The second part of the paper uses a patent renewal model based on the seminal work of Pakes and Schankerman (1984) to estimate the private value of innovations owned by EIF-supported VC investees. The value of individual innovations is characterised by a large degree of heterogeneity, with values ranging from just a few hundred Euro to outliers exceeding EUR 400m. Importantly, these findings relate to the *private* value of patent protection, which is to be interpreted as the additional financial return resulting from the patent's protection of the underlying intellectual property. As such, these estimates are likely to be the lower bound of the total social return, since the latter would include externalities such as non-appropriable knowledge-spillovers.

A comparison of innovations values over start-up industries and technology areas reveals that innovations stemming from the life sciences industry are, on average, more valuable than in other innovation areas. However, we also consistently observe a negative relationship between the *innovative propensity* of patentors in a given industry and the median value of patented innovations. Lower propensity to patent is correlated to a "shortage" of low-valued innovations that may be indicative to stronger barriers to patenting and can be observed in some sectors and geographies.

We further compare the value of patented innovations to the date of the EIF-backed VC investment which, due to the nature of our sample, typically represents the date of the initial VC round for the start-up. Interestingly, we find that innovations initiated prior to the date of VC investment are significantly more valuable than post-investment innovations. This result is valid both for initial and follow-on innovations, and is robust to a series of controlling factors. We discuss two potential explanations for this, noting that prior research on the effects of VC investments is mostly restricted to post-investment innovation, neglecting a potentially extra channel for VC investors to affect start-ups.

Finally, we compare EIF-supported financing with start-ups' innovative output, producing an "innovation multiplier" linking inputs and outputs of the EIF VC activity. While such indicator bears no virtue of causality, it allows to assess the capacity of VC-backed start-ups to transform financial into innovative capital. The analysis shows that for every Euro of VC financing flowing into EIF-backed start-ups, investees were able to create 2.74 EUR of private value via patented innovations.

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Appendices

A Concordance between IPC and Invest Europe sectoral classification

Table A1: IPC to Invest Europe sectoral classification

Macro-sector	Invest Europe activity sector	IPC section	IPC classes
ICT	ICT	G	Measuring; Testing (G01). Computing; Calculating; Counting (G06). Educating; Cryptography; Display; Advertising; Seals (G09). Information storage (G11).
		H	Electric communication technique (H04).
Life Sciences	Life sciences & Biotech	A	Medical or veterinary science; Hygiene (A61).
		C	Organic chemistry (C07). Organic macromolecular compounds; Their preparation or chemical working up; Compositions based thereon (C08). Biochemistry; Beer; Spirits; Wine; Vinegar; Microbiology; Enzymology; Mutation or genetic engineering (C12).
Electronics	Other Electronics	B	Generating or transmitting mechanical vibrations in general (B06).
		G	Optics (G02). Photography; Cinematography; Analogous techniques using waves other than optical waves; Electrography; Holography (G03). Horology (G04). Controlling; Regulating (G05). Checking devices (G07). Signalling (G08). Musical instruments; Acoustics (G10). Instrument details (G12).
		H	Basic electric elements (H01). Basic electronic circuitry (H03). Electric techniques not otherwise provided for (H05).
Other	Agriculture & Food related	A	Agriculture; Forestry; Animal husbandry; Hunting; Trapping; Fishing (A01). Baking; Equipment for making or processing doughs; Doughs for baking (A21). Butchering; Meat treatment; Processing poultry or fish (A22). Foods or foodstuffs; Their treatment, not covered by other classes (A23). Subject matter not otherwise provided for in this section (A99).
		C	Animal or vegetable oils, fats, fatty substances or waxes; Fatty acids therefrom; Detergents; Candles (C11). Sugar industry (C13).
Other	Chemicals and Materials	B	Physical or chemical processes or apparatus in general (B01). Centrifugal apparatus or machines for carrying out physical or chemical processes (B04). Casting; Powder metallurgy (B22). Nano technology (B82).
		C	Inorganic chemistry (C01). Glass; Mineral or slag wool (C03). Fertilisers; Manufacture thereof (C05). Explosives; Matches (C06). Dyes; Paints; Polishes; Natural resins; Adhesives; Compositions not otherwise provided for; Applications of materials not otherwise provided for (C09). Petroleum, gas or coke industries; Technical gases containing carbon monoxide; Fuels; Lubricants; Peat (C10). Metallurgy; Ferrous or non ferrous alloys; Treatment of alloys or non ferrous metals (C22). Coating metallic material; Coating material with metallic material; Chemical surface treatment; Diffusion treatment of metallic material; Coating by vacuum evaporation, by sputtering, by ion implantation or by chemical vapour deposition, in general; Inhibiting corrosion of metallic material or incrustation in general (C23). Electrolytic or electrophoretic processes; Apparatus therefor (C25). Crystal growth (C30).
		D	Natural or artificial threads or fibres; Spinning (D01).
Other	Construction/Transports	B	Working cement, clay, or stone (B28). Vehicles in general (B60). Railways (B61). Land vehicles for travelling otherwise than on rails (B62). Ships or other waterborne vessels; Related equipment (B63). Aircraft; Aviation; Cosmonautics (B64).
		C	Cements; Concrete; Artificial stone; Ceramics; Refractories (C04).
		E	Construction of roads, railways, or bridges (E01). Building (E04). Earth or rock drilling; Mining (E21).

(Table A1 continued)

Macro-sector	Invest Europe activity sector	IPC section	IPC classes
Other	Energy and Environment	B	Disposal of solid waste; Reclamation of contaminated soil (B09).
		C	Treatment of water, waste water, sewage, or sludge (C02).
		E	Water supply; Sewerage (E03).
		F	Combustion engines; Hot gas or combustion product engine plants (F02). Storing or distributing gases or liquids (F17). Lighting (F21). Steam generation (F22). Combustion apparatus; Combustion processes (F23). Heating; Ranges; Ventilating (F24).
		G	Nuclear physics; Nuclear engineering (G21).
		H	Generation, conversion, or distribution of electric power (H02).
Other	Industrial Products	B	Crushing, pulverising, or disintegrating; Preparatory treatment of grain for milling (B02). Separation of solid materials using liquids or using pneumatic tables or jigs; Magnetic or electrostatic separation of solid materials from solid materials or fluids; Separation by high voltage electric fields (B03). Spraying or atomising in general; Applying liquids or other fluent materials to surfaces, in general (B05). Separating solids from solids; Sorting (B07). Cleaning (B08). Mechanical metal working without essentially removing material; Punching metal (B21). Machine tools; Metal working not otherwise provided for (B23). Grinding; Polishing (B24). Hand tools; Portable power driven tools; Handles for hand implements; Workshop equipment; Manipulators (B25). Hand cutting tools; Cutting; Severing (B26). Working or preserving wood or similar material; Nailing or stapling machines in general (B27). Working of plastics; Working of substances in a plastic state in general (B29). Presses (B30). Making paper articles; Working paper (B31). Layered products (B32). Additive manufacturing technology (B33). Printing; Lining machines; Typewriters; Stamps (B41). Bookbinding; Albums; Files; Special printed matter (B42). Writing or drawing implements; Bureau accessories (B43). Conveying; Packing; Storing; Handling thin or filamentary material (B65). Hoisting; Lifting; Hauling (B66). Opening or closing bottles, jars or similar containers; Liquid handling (B67). Saddlery; Upholstery (B68). Micro structural technology (B81).
		C	Skins; Hides; Pelts; Leather (C14). Metallurgy of iron (C21). Combinatorial technology (C40).
		D	Yarns; Mechanical finishing of yarns or ropes; Warping or beaming (D02). Weaving (D03). Sewing; Embroidering; Tufting (D05). Treatment of textiles or the like; Laundering; Flexible materials not otherwise provided for (D06). Ropes; Cables other than electric (D07). Paper making; Production of cellulose (D21).
		E	Hydraulic engineering; Foundations; Soil shifting (E02).
		F	Machines or engines in general; Engine plants in general; Steam engines (F01). Machines or engines for liquids; Wind, spring, or weight motors; Producing mechanical power or a reactive propulsive thrust, not otherwise provided for (F03). Positive displacement machines for liquids; Pumps for liquids or elastic fluids (F04). Fluid pressure actuators; Hydraulics or pneumatics in general (F15). Engineering elements or units; General measures for producing and maintaining effective functioning of machines or installations; Thermal insulation in general (F16). Refrigeration or cooling; Combined heating and refrigeration systems; Heat pump systems; Manufacture or storage of ice; Liquefaction or solidification of gases (F25). Drying (F26). Furnaces; Kilns; Ovens; Retorts (F27). Heat exchange in general (F28). Weapons (F41). Ammunition; Blasting (F42).
Other	Consumer Products	A	Tobacco; Cigars; Cigarettes; Smokers' requisites (A24). Wearing apparel (A41). Headwear (A42). Footwear (A43). Haberdashery; Jewellery (A44). Hand or travelling articles (A45). Brushware (A46). Furniture; Domestic articles or appliances; Coffee mills; Spice mills; Suction cleaners in general (A47). Life saving; Fire fighting (A62). Sports; Games; Amusements (A63).
		B	Decorative arts (B44).
		D	Braiding; Lace making; Knitting; Trimmings; Non woven fabrics (D04).
		E	Locks; Keys; Window or door fittings; Safes (E05). Doors, windows, shutters, or roller blinds, in general; Ladders (E06).

B Identification of key innovation fields

Sections 2 and 3.2 mentioned the unsuitability of the International Patent Classification (IPC) to identify key technology areas for innovations of EIF-backed start-ups. Against this background, we discuss here an alternative classification methodology, based on the text mining of patent abstracts. The approach mainly relies on established statistical approaches to perform feature extraction of complex highly-dimensional data (*i.e.* free-form text), complemented by a manual validation and final aggregation stage. A key benefit of this strategy is that the final result is elicited from the data itself, as opposed to a static, *ex-ante* defined set of technology areas.

For simplicity, we limited the analysis to English-written abstracts, based on the fact that for most innovations we could find at least one main or *equivalent* patent publication drafted in English. Nevertheless, this choice narrowed the initial set of innovations from 14,292 to 12,187. For each abstract, we identified the top three salient *n*-grams[32] using the Rapid Automatic Keyword Extraction (RAKE) algorithm of Rose *et al.* (2010). Overall, we obtained 24,663 unique sets of keywords.

To further reduce the dimensionality of the data, we matched each keyword set to its (potential) Wikipedia page, using Wikipedia's own search engine API. The matching of keywords to Wikipedia's articles bears two particular benefits. First, it allows to "validate" the salience of a given keyword. Second, it allows to embed patents' abstracts within Wikipedia's taxonomic structure, consisting *inter alia* of *categories*. These are defined as "groups of articles on similar topics".[33] To counter potential errors in the matching process, we manually validated each category, excluding those reported less than 30 times. We obtained 307 categories, covering 12,887 keywords and 9,424 innovations.

The last step of the analysis, shrinking 307 categories to 20 technology areas, was entirely manual.[34] To overcome the complexity brought by broader categories that could be considered *transversal* to various technology fields (*e.g.* is "software" more related to computer networks or mobile technologies?), we developed a scoring system to assess the proximity of each concept *vis-à-vis* a given technology area. The scoring system is based on two elements: the breadth/specificity of the category (*e.g.* while the term "neurotransmitter" is considered very specific, the term "surgery" is much more broad and transversal) as well a subjective proximity score. The combination of the two measures underlies Table B1, where for each technology field we list all categories with non-zero proximity scores (ranked by weight). Finally, we computed the total category-based score between each patent family and the given technology area, selecting as a reference the field with the highest score.

While this aggregation process is inherently subjective and *ad-hoc*, a number of consistency measures have been adopted. Most notably, the final classification is mostly consistent with the sectoral categories discussed in Appendix A (*e.g.* *Oncology* patents almost always in the *Life science* class).

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[32] An *n*-gram is a sequence of contiguous words in a text. For reasons of processing power, we limited the analysis to series of maximum five words, or *five*-grams.

[33] Wikipedia: Categories FAQ

[34] A number of attempts to use statistical methods relying on network theory were made (*e.g.* network centrality measures, Louvain method for community detection). These exploited the distance, in terms of hyperlinks, needed to *navigate* from one Wikipedia's article to the other. While some automated strategies produced promising results that fed into the manual analysis, none of these was entirely satisfactory.

Table B1: Technology field scoring system

Technology field	Related categories (level of breadth: 1 = very broad, 4 = very specific)
Oncology	**High score:** Cloning (4), DNA Replication (4), Fibrate (4), Gene Delivery (4), Genetic Engineering (4), Polymerase Chain Reaction (4), Purine (4), RNA (4), Stem Cell (4), Breast Cancer (3), Carcinogen (3), Lung Cancer (3); **Medium:** Cofactor (Biochemistry) (4), Microarray (4), Protease (4), Transferase (4), Genomics (3), Mutation (3), DNA (2), Gene Expression (2), Proteomics (2), Radiobiology (2); **Low:** Apoptosis (3), Enzyme (3), Genetic Disorder (3), Polymer (3), Bioinformatics (2), Enzyme Kinetics (2), Molecular Genetics (2), Polymer Chemistry (2), Tissue Engineering (2), Biochemistry (1), Biomaterial (1), Electrophysiology (1), Epigenetics (1), Helix (1), Nucleic Acid (1), Nucleotide (1), Oncology (1), Pyridine (1).
Metabolic disorders	**High:** Cofactor (Biochemistry) (4), Cytokine (4), Fibrate (4), Lymphocyte (4), Protease (4), T Cell (4), Transferase (4), Diabetes Mellitus (3), Genetic Disorder (3); **Medium:** Cloning (4), DNA Replication (4), Dermatology (4), Endocrine System (4), Gene Delivery (4), Genetic Engineering (4), Glycoprotein (4), Microarray (4), Polymerase Chain Reaction (4), Purine (4), RNA (4), Signal Transduction (4), Stem Cell (4), Zwitterion (4), Enzyme (3), Steroid (3), Anorectic (2), Bioinformatics (2), Enzyme Kinetics (2), Radiobiology (2); **Low:** Alkaloid (3), Amino Acid (3), Aphrodisiac (3), Apoptosis (3), B Vitamins (3), Cellular Respiration (3), Dietary Supplement (3), Genomics (3), Growth Factor (3), Microtechnology (3), Mutation (3), Nanotechnology (3), Narcolepsy (3), Polymer (3), Protein (3), Smoking (3), Biophysics (2), DNA (2), Gene Expression (2), Molecular Biology (2), Molecular Genetics (2), Organic Acid (2), Polymer Chemistry (2), Proteomics (2), Receptor (Biochemistry) (2), Synthetic Biology (2), Systems Biology (2), Tissue Engineering (2), Alcohol (1), Amine (1), Analytical Chemistry (1), Anatomical Pathology (1), Angiology (1), Antibody (1), Biochemistry (1), Biological Engineering (1), Biomaterial (1), Cell Signaling (1), Chemical Engineering (1), Colloid (1), Electrophysiology (1), Epigenetics (1), Evolutionary Biology (1), Food Additive (1), Health Technology (1), Helix (1), Histopathology (1), Lactam (1), Lipid (1), Medical Physics (1), Metabolism (1), Nucleic Acid (1), Nucleotide (1), Nutrition (1), Organelle (1), Pediatrics (1), Peptide (1), Physiology (1), Prokaryote (1), Prosthesis (1), Pyrrole (1), Solution (1), Surgery (1), Syndrome (1).
Electronic devices	**High:** Electromagnetic Compatibility (4), Electromagnetic Spectrum (4), Molecular Electronics (4), Photovoltaics (4), Radar (4), Semiconductor Device (4), Sensor (4), Videogame (4), Electrode (3), Integrated Circuit (3), Liquid Crystal (3), Phase Transition (3), Semiconductor (3); **Medium:** Holography (4), Optical Fiber (4), Plasma (Physics) (4), Soft Matter (4), Spacecraft (4), Capacitor (3), Microtechnology (3), Nanotechnology (3), Power Electronics (3), Dielectric (2), Digital Electronics (2), Display Technology (2), Electricity (2), Electrostatics (2), Magnetism (2), Spintronics (2); **Low:** Energy Storage (3), Particle Physics (3), Color (2), Energy Transformation (2), Oscillation (2), Quantum Optics (2), Vehicle Technology (2), Optoelectronics (1), Photonics (1), Quantum Electrodynamics (1).
Medtech	**High:** Chromatography (4), Cloning (4), Microarray (4), Neuroimaging (4), Stem Cell (4), Image Processing (3), Microtechnology (3), Nanotechnology (3); **Medium:** DNA Replication (4), Dementia (4), Gene Delivery (4), Genetic Engineering (4), Polymerase Chain Reaction (4), Purine (4), RNA (4), Mass Spectrometry (3), Measuring Instrument (3), Bioinformatics (2), Biomedical Engineering (2), Biophysics (2), Blood Test (2), Medical Imaging (2), Radiobiology (2), Synthetic Biology (2), Systems Biology (2), Tissue Engineering (2); **Low:** Ageing (3), Apoptosis (3), Cellular Respiration (3), Genomics (3), Mutation (3), Polymer (3), DNA (2), Gene Expression (2), Gerontology (2), Molecular Biology (2), Molecular Genetics (2), Polymer Chemistry (2), Receptor (Biochemistry) (2), Senescence (2), Adhesive (1), Alcohol (1), Analytical Chemistry (1), Anatomical Pathology (1), Biochemistry (1), Biological Engineering (1), Biomaterial (1), Chalcogen (1), Chemical Engineering (1), Electrophysiology (1), Elementary Particle (1), Epigenetics (1), Gel (1), Health Technology (1), Medical Physics (1), Metalloid (1), Neurochemistry (1), Nucleic Acid (1), Nucleotide (1), Prosthesis (1), Pyridine (1), Pyrrole (1), Refrigerant (1), Solution (1), Solvent (1).
Neurology, psychiatry pathologies	**High:** Carbamate (4), Dementia (4), Neuroimaging (4), Nootropic (4), Signal Transduction (4), Substituted Amphetamine (4), Substituted Phenethylamine (4), Amphetamine (3), Aphrodisiac (3), Cerebellum (3), Narcolepsy (3), Neurotransmitter (3), Opioid (3), Stimulant (3); **Medium:** Ageing (3), Alkaloid (3), Anorectic (2), Central Nervous System (2), Euphoria (2), Exercise Physiology (2), Gerontology (2), Learning Disability (2), Senescence (2); **Low:** Carcinogen (3), Smoking (3), Bioinformatics (2), Radiobiology (2), Reducing Agent (2), Toxicology (2), Abnormal Psychology (1), Alcohol (1), Chloride (1), Neurochemistry (1), Neurology (1), Neurophysiology (1), Neuroscience (1), Organic Chemistry (1), Organofluorine Chemistry (1), Physical Chemistry (1), Quantum Chemistry (1), Stereochemistry (1), Surgery (1).
Broadcasting	**High:** Signal Processing (4), Data Transmission (3), Digital Television (3), Noise (3), Signage (3); **Medium:** Multiplexing (4), Round-Trip Delay Time (4), Videotelephony (4), Digital Signal Processing (3), Amplifier (2), Broadcast Engineering (2), Communications Protocol (2), Media Technology (2), Telecommunication (2), Transducer (2), Wireless (2); **Low:** Digital Audio (3), Mobile Telephony (3), Display Technology (2), Internet Protocol Suite (2), Internet Standard (2), Wireless Network (2), Computer Network (1), Mobile Technology (1), Radio (1), Radio Resource Management (1), Technical Communication (1), Telecommunications Engineering (1), Telecommunications Equipment (1), Wave (1), Waves (1).
Audio & video	**High:** Computer Graphics (4), Holography (4), Signal Processing (4), Videogame (4), Videotelephony (4), Acoustics (3), Digital Audio (3), Digital Television (3), Liquid Crystal (3), Noise (3); **Medium:** Virtual Reality (4), Digital Photography (3), Digital Signal Processing (3), Amplifier (2), Color (2), Display Technology (2), Media Technology (2); **Low:** Data Transmission (3), Mobile Telephony (3), Optical Filter (3), Signage (3), Telephony (2), Mobile Technology (1), Radio (1), Wave (1), Waves (1).
Information security, financial technology	**High:** Cryptography (4), E-Commerce (4), Privacy (3); **Medium:** Videogame (4); **Low:** Data Transmission (3), Media Technology (2), Software (2), Computer Network (1).

(Table B1 continued)

Technology field	Related categories (level of breadth: 1 = very broad, 4 = very specific)
Computer network, ubiquitous computing	**High:** Holography (4), Multiplexing (4), Round-Trip Delay Time (4), Signal Processing (4), Ubiquitous Computing (4), Videogame (4), Virtual Reality (4), Human-Computer Interaction (3); **Medium:** Cryptography (4), E-Commerce (4), Global Positioning System (4), Digital Signal Processing (3), Optical Filter (3), Central Processing Unit (2), Communications Protocol (2), Ethernet (2), Internet Protocol Suite (2), Internet Standard (2), Wireless Network (2); **Low:** Data Transmission (3), Digital Television (3), Parallel Computing (3), Privacy (3), Synchronization (3), Broadcast Engineering (2), Digital Electronics (2), Display Technology (2), Software (2), Wireless (2), Computer Architecture (1), Computer Memory (1), Computer Network (1), Control Theory (1), Data Management (1), Embedded System (1), Information Theory (1), Network Architecture (1).
Transports	**High:** Aerodynamics (4), Avionics (4), Radar (4), Spacecraft (4); **Medium:** Vehicle Technology (2); **Low:** Piping (3).
Infectious diseases	**High:** Lymphocyte (4), T Cell (4); **Medium:** Signal Transduction (4), Alkaloid (3), Other Disease (3); **Low:** Antibacterial (1), Antibody (1), Bacteria (1), Bacteriology (1), Biological Engineering (1), Chemical Synthesis (1), Colloid (1), Disinfectant (1), Drug Discovery (1), Evolutionary Biology (1), Histopathology (1), Immune System (1), Lactam (1), Neurochemistry (1), Organelle (1), Pharmacodynamics (1), Pharmacokinetics (1), Pharmacology (1), Prokaryote (1), Vaccine (1), Virus (1).
Innovative materials	**High:** Crystal (4), Metamaterial (4), Plasma (Physics) (4), Soft Matter (4), Thermoplastic (4), Thin Film (4), Coating (3), Crystallography (3), Fluid Mechanics (3), Organic Semiconductor (3), Transition Metal (3), Vacuum (3); **Medium:** Aerodynamics (4), HVAC (4), Molecular Electronics (4), Photovoltaics (4), Semiconductor Device (4), Sensor (4), Spacecraft (4), Ventilation (Architecture) (4), Fluid Dynamics (3), Particle Physics (3), Phase Transition (3), Semiconductor (3), Thermodynamics (3), Abrasive (2), Fluorescence (2), Magnetism (2), Oscillation (2), Reducing Agent (2); **Low:** Liquid Crystal (3), Microtechnology (3), Nanotechnology (3), Heat Transfer (2), Vehicle Technology (2), Condensed Matter Physics (1), Nitrogen Cycle (1), Quantum Electrodynamics (1).
Mobile technologies	**High:** Global Positioning System (4), Videotelephony (4), Virtual Reality (4), Digital Signal Processing (3), Mobile Telephony (3); **Medium:** E-Commerce (4), Holography (4), Multiplexing (4), Radar (4), Videogame (4), Human-Computer Interaction (3), Communications Protocol (2), Digital Electronics (2), Display Technology (2), Software (2), Telephony (2), Wireless (2), Wireless Network (2); **Low:** Acoustics (3), Data Transmission (3), Liquid Crystal (3), Signage (3), Synchronization (3), Internet Protocol Suite (2), Mobile Technology (1), Radio (1), Radio Resource Management (1), Technical Communication (1).
Autoimmune diseases	**High:** Carbamate (4), Lymphocyte (4), T Cell (4), Autoimmune Disease (3); **Medium:** Cloning (4), DNA Replication (4), Gene Delivery (4), Genetic Engineering (4), Microarray (4), Polymerase Chain Reaction (4), Purine (4), RNA (4), Signal Transduction (4), Stem Cell (4); **Low:** Apoptosis (3), Carcinogen (3), Genomics (3), Mutation (3), Smoking (3), Biophysics (2), DNA (2), Gene Expression (2), Proteomics (2), Reducing Agent (2), Synthetic Biology (2), Systems Biology (2), Toxicology (2), Analytical Chemistry (1), Biomaterial (1), Chemical Engineering (1), Chemical Synthesis (1), Epigenetics (1), Immune System (1), Immunology (1), Neurochemistry (1), Nucleic Acid (1), Nucleotide (1), Organic Chemistry (1), Organofluorine Chemistry (1), Physical Chemistry (1), Quantum Chemistry (1), Stereochemistry (1), Vaccine (1).
Other pathologies	**High:** Dermatology (4), Endocrine System (4); **Medium:** Chromatography (4), Glycoprotein (4), Zwitterion (4), Other Disease (3), Smoking (3); **Low:** Amino Acid (3), Growth Factor (3), Mass Spectrometry (3), Measuring Instrument (3), Polymer (3), Protein (3), Polymer Chemistry (2), Tissue Engineering (2), Adhesive (1), Amine (1), Biological Engineering (1), Chalcogen (1), Elementary Particle (1), Gel (1), Histopathology (1), Lipid (1), Metalloid (1), Oxygen (1), Peptide (1), Prosthesis (1), Pyrrole (1), Refrigerant (1), Solution (1), Solvent (1), Surgery (1).
Nutrition, botanics	**High:** Phenol (4), Phenols (4), Photosynthesis (4), Plant Physiology (4), B Vitamins (3), Dietary Supplement (3); **Medium:** Botany (2), Organic Acid (2); **Low:** Food Additive (1), Nutrition (1).
Alternative energy sources	**High:** Fuel Cell (4), Photovoltaics (4), Renewable Energy (4), Electromagnetic Radiation (3), Energy Storage (3), Radioactive Decay (3); **Medium:** Spectroscopy (3), Diffraction (2), Energy Transformation (2), Radiation (2), Scattering (2); **Low:** Electrode (3), Piping (3), Power Electronics (3), Electricity (2), Heat Transfer (2), Magnetism (2), Spintronics (2), Vehicle Technology (2).
Cardiovascular, hematology, traumatology pathologies	**High:** Cardiovascular Disease (4); **Medium:** Fibrate (4), Glycoprotein (4), Ageing (3), Smoking (3), Steroid (3), Blood Test (2), Gerontology (2), Radiobiology (2), Senescence (2), Toxicology (2); **Low:** Alkaloid (3), Growth Factor (3), Microtechnology (3), Nanotechnology (3), Other Disease (3), Polymer (3), Protein (3), Bioinformatics (2), Polymer Chemistry (2), Reducing Agent (2), Alcohol (1), Anatomical Pathology (1), Angiology (1), Cardiology (1), Chemical Synthesis (1), Colloid (1), Health Technology (1), Hematology (1), Organic Chemistry (1), Organofluorine Chemistry (1), Physical Chemistry (1), Prosthesis (1), Quantum Chemistry (1), Stereochemistry (1), Surgery (1), Traumatology (1).
Lasers	**High:** Optical Fiber (4), Laser (3), Light-Emitting Diode (3); **Medium:** Electromagnetic Compatibility (4), Electromagnetic Spectrum (4), Holography (4), Plasma (Physics) (4), Liquid Crystal (3), Particle Physics (3), Color (2), Quantum Optics (2); **Low:** Electrode (3), Phase Transition (3), Spectroscopy (3), Diffraction (2), Digital Electronics (2), Electricity (2), Magnetism (2), Oscillation (2), Radiation (2), Spintronics (2), Optoelectronics (1), Photonics (1), Quantum Electrodynamics (1).
Construction & architecture	**High:** HVAC (4), Spacecraft (4), Ventilation (Architecture) (4), Piping (3), Thermodynamics (3); **Medium:** Thermoplastic (4), Heat Transfer (2); **Low:** Fluid Dynamics (3), Fluid Mechanics (3).

C A model of patent renewal and value

This appendix tackles the theoretical underpinnings of our value estimation of EIF-backed innovations. As discussed in section 2, innovations are proxied by "simple" patent families as reported by the EPO-PATSTAT database (EPO, 2017, p.22). We define $IV_k \in \Re$, *i.e.* innovation k's private value as the sum of all returns accruing to the innovation holder as long as innovation rights are in force. This also assumes that innovations have no positive (nor negative) externalities. As in Deng (2007), we postulate that IV_k is equivalent to the cumulative value of all patents within the given family:

$$IV_k = \sum_{j=1}^{J} PV_j \tag{1}$$

where $PV_j \in \Re$ is the value of patent j. To estimate PV_j, we assign a functional form to patent returns.

Following Pakes and Schankerman (1984), we thus assume that returns from patent ownership $r(t)$ follow an exponential curve with constant decay rate δ:

$$r(t) = r_0 e^{-\delta t} \tag{2}$$

where r_0 represents the initial appropriable revenues of a given patent. The costs of patenting can be either fixed or variable. In the application phase, fixed costs play a significant role in discouraging potential patentors to submit unprofitable inventions. This role is unmeasurable in our exercise, since we only observe inventions whose initial patenting costs have been covered. In the post-application stage patentors must pay periodical renewal fees if they wish their patenting rights to be maintained. These may be paid until the maximum renewal period T,[35] after which all existing rights expire. Renewal costs $c(t) = \{c_t\}$, $c'(t) \geq 0$ are a sequence of non-decreasing fees to preserve IP rights.

Against this background, at the beginning of every period[36] t_i, $i = 0, 1, \ldots, T$ patent owners must choose whether to pay the renewal fee or face the lapse of their patenting rights. Assuming perfect information and rational agents, the decision to renew at time t_i is only justified if the returns accruing in $[t_i, t_{i+1}]$ at least offset the renewal costs c_{t_i}, *i.e.* if

$$\int_{t_i}^{t_{i+1}} r(t) e^{-s\tau} d\tau \geq c_{t_i} \tag{3}$$

where s is the discount rate defining the time value of revenues. Substituting (2) in (3) yields:

$$r_0 \int_{t_i}^{t_{i+1}} e^{-(s+\delta)\tau} d\tau \geq c_{t_i} \tag{4}$$

[35] Despite some noteworthy exceptions (*e.g.* Japan, Israel), this limit is typically 20 years.

[36] This cumbersome notation is made necessary by the subtle difference between renewal *time* t and renewal *period* i. While most EU patent offices demand annual renewal fees, this may not be the case elsewhere: *e.g.* the USPTO foresees a set of 3 renewal fees, due at 3.5, 7.5 and 11.5 years after application.

Define $\lambda \in [0, T]$ as the last renewal period, after which the patent lapses. By our prior assumptions:

$$\begin{cases} c_{t_\lambda} \leq r_0 \displaystyle\int_{t_\lambda}^{t_{\lambda+1}} e^{-(s+\delta)\tau} d\tau \\ c_{t_{\lambda+1}} > r_0 \displaystyle\int_{t_{\lambda+1}}^{t_{\lambda+2}} e^{-(s+\delta)\tau} d\tau \end{cases} \tag{5}$$

i.e. patent revenues in $[t_\lambda, t_{\lambda+1}]$ are higher than renewal costs c_{t_λ}, while those in $[t_{\lambda+1}, t_{\lambda+2}]$ are lower than or equivalent to $c_{t_{\lambda+1}}$.[37] Solving the lower- and upper-bound of (5) for r_0 yields:

$$\begin{cases} r_0 \geq \dfrac{s+\delta}{1 - e^{-(s+\delta)\Delta_{\lambda+1}}} c_{t_\lambda} e^{(s+\delta)t_\lambda} \\ r_0 < \dfrac{s+\delta}{1 - e^{-(s+\delta)\Delta_{\lambda+2}}} c_{t_{\lambda+1}} e^{(s+\delta)t_{\lambda+1}} \end{cases} \tag{6}$$

where $\Delta_{\lambda+m} = t_{\lambda+m} - t_{\lambda+(m-1)}$. The total (discounted) revenue stream of the patent $PR \in \Re$ is thus:

$$PR = r_0 \int_{t_0}^{t_{\lambda+1}} e^{-(s+\delta)\tau} d\tau \tag{7}$$

By assuming $t_0 = 0$, solving for the integral in (7) and plugging (6) yields:

$$\begin{cases} PR \geq e^{(s+\delta)t_\lambda} \dfrac{1 - e^{-(s+\delta)t_{\lambda+1}}}{1 - e^{-(s+\delta)\Delta_{\lambda+1}}} c_{t_\lambda} \\ PR < e^{(s+\delta)t_{\lambda+1}} \dfrac{1 - e^{-(s+\delta)t_{\lambda+2}}}{1 - e^{-(s+\delta)\Delta_{\lambda+2}}} c_{t_{\lambda+1}} \end{cases} \Rightarrow z_{t_\lambda} c_{t_\lambda} \leq PR < z_{t_{\lambda+1}} c_{t_{\lambda+1}} \tag{8}$$

where $z_{t_{\lambda+m}} = z\left(\delta, s, t_{\lambda+m}, t_{\lambda+(m+1)}\right)$. As in Bessen (2008), we assume s at 10% per annum.

To estimate δ, the revenue depreciation rate, we must set a parametric form for the distribution of patent values. A number of studies (see Bessen, 2008; Schankerman and Pakes, 1986) show evidence that the lognormal distribution provides the closest fit to invention values as well as patent renewal data. Assume that PR_j — the total revenue from patent $j = 1, 2, \ldots J$ — is a random variable following a lognormal distribution,[38] determined by:

$$\ln\left(PR_j\right) = \mathbf{x}_j \beta + \varepsilon_j, \quad \varepsilon_j | \mathbf{x} \sim N\left(0, \sigma_\varepsilon\right) \tag{9}$$

where $\mathbf{x}_j$ is a vector of patent characteristics. The quantity $\ln\left(PR_j\right)$ cannot be observed, *i.e.* it is *latent*. Instead, we observe $\lambda_j \in [0, T]$, *i.e.* the last renewal period for patent j. The observable

[37] This leads to the conclusion that patents reaching their maximum holding period T are *right-censored*, for only the lower-bound of accruing returns can be estimated. It is perhaps then useful to assume that $c_{T+1} = \infty$ so that no amount of revenues in $[T, T+1]$ can offset renewal costs.

[38] In most cited works such assumption typically concerns the initial return r_0. However, it can be easily proven that if the quantity r_0 is log-normally distributed, so is PR as per Equation 7.

variable λ_j constitutes an *ordered response* taking values $\{0, 1, 2, \ldots, T\}$ such that:

$$\begin{aligned}
\lambda_j = 0 \quad & \text{if } \ln\left(PV_j\right) < \ln\left(z_{t_1} c_{t_1}\right) \\
\lambda_j = 1 \quad & \text{if } \ln\left(z_{t_1} c_{t_1}\right) \leq \ln\left(PV_j\right) < \ln\left(z_{t_2} c_{t_2}\right) \\
& \vdots \\
\lambda_j = T \quad & \text{if } \ln\left(PV_j\right) \geq \ln\left(z_{t_T} c_{t_T}\right)
\end{aligned} \tag{10}$$

Plugging (9), the conditional distribution of λ_j given $\mathbf{x}_j$ becomes:

$$\begin{aligned}
P\left(\lambda_j = 0|\mathbf{x}_j\right) &= P\left(\mathbf{x}_j\beta + \varepsilon_j < \ln\left(z_{t_1} c_{t_1}\right)|\mathbf{x}_j\right) = \Phi\left(\left(\ln\left(z_{t_1} c_{t_1}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) \\
P\left(\lambda_j = 1|\mathbf{x}_j\right) &= \Phi\left(\left(\ln\left(z_{t_2} c_{t_2}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) - \Phi\left(\left(\ln\left(z_{t_1} c_{t_1}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) \\
& \vdots \\
P\left(\lambda_j = T|\mathbf{x}_j\right) &= 1 - \Phi\left(\left(\ln\left(z_{t_T} c_{t_T}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right)
\end{aligned} \tag{11}$$

where Φ is the cumulative standard normal distribution function. The conditional probabilities in (11) depend on the parameters β, σ_ε and δ and can be estimated via maximum likelihood (MLE). Following Wooldridge (2001), the log-likelihood function of each patent j is:

$$\begin{aligned}
\ell_j\left(\delta, \sigma_\varepsilon, \beta\right) = 1\left[\lambda_j = 0\right] \ln\left[\Phi\left(\left(\alpha_1 - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right)\right] \\
+ 1\left[\lambda_j = 1\right] \ln\left[\Phi\left(\left(\alpha_2 - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) - \Phi\left(\left(\alpha_1 - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right)\right] \\
+ \ldots + 1\left[\lambda_j = T\right] \ln\left[1 - \Phi\left(\left(\alpha_T - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right)\right]
\end{aligned} \tag{12}$$

where $\alpha_i = \ln\left(z_{t_i} c_{t_i}\right)$. We can see that (12) defines the log-likelihood of an *ordered probit model*.

Working with recent patent vintages poses one additional issue, as pointed out by Gupeng and Xiangdong (2012). That is, the value estimation of a patent that is currently active and whose T-year renewal window has yet to conclude will suffer from *right censoring*, *i.e.* the inability to observe its future renewal pattern. The authors address this issue by updating the model specification to include the censoring variable η_j, which has value 1 if the patent renewal window is right-censored, and 0 otherwise. As a result, for a given last renewal period $i \in (0, T)$, Equation 11 is updated as follows:

$$\begin{cases}
P\left(\lambda_j = i|\mathbf{x}_j\right) = \Phi\left(\left(\ln\left(z_{t_{i+1}} c_{t_{i+1}}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) - \Phi\left(\left(\ln\left(z_{t_i} c_{t_i}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) & \text{if } \eta_j = 0 \\
P\left(\lambda_j = i|\mathbf{x}_j\right) = 1 - \Phi\left(\left(\ln\left(z_{t_i} c_{t_i}\right) - \mathbf{x}_j\beta\right)\sigma_\varepsilon^{-1}\right) \quad \text{if } \eta_j = 1
\end{cases} \tag{13}$$

To calculate patent values based on the MLE estimates of β, σ_ε and δ, we must derive the expected log-value of patent j, conditional on the observed last renewal period λ. Using Equations 8 and 9 and applying the formula for the conditional expectation, this can be written as:

$$E\left(\ln\left(PV_j\right)\left|\ln\left(z_{t_\lambda}c_{t_\lambda}\right) < \ln\left(PV_j\right) \leq \ln\left(z_{t_{\lambda+1}}c_{t_{\lambda+1}}\right)\right.\right) = \mathbf{x}_j\beta + E\left(\varepsilon_j\left|a < \varepsilon_j \leq b\right.\right) \tag{14}$$
$$= \mathbf{x}_j\beta + \sigma_\varepsilon \frac{\phi\left(\frac{a}{\sigma_\varepsilon}\right) - \phi\left(\frac{b}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{b}{\sigma_\varepsilon}\right) - \Phi\left(\frac{a}{\sigma_\varepsilon}\right)}$$

where $a = \ln\left(z_{t_\lambda}c_{t_\lambda}\right) - \mathbf{x}_j\beta$, $b = \ln\left(z_{t_{\lambda+1}}c_{t_{\lambda+1}}\right) - \mathbf{x}_j\beta$ and ϕ indicates the standard normal distribution density function. When the value of the patent is right-censored, (14) becomes:

$$E\left(\ln\left(PV_j\right)\left|\ln\left(z_{t_\lambda}c_{t_\lambda}\right) < \ln\left(PV_j\right)\right.\right) = \mathbf{x}_j\beta + \sigma_\varepsilon \frac{\phi\left(\frac{a}{\sigma_\varepsilon}\right)}{1 - \Phi\left(\frac{a}{\sigma_\varepsilon}\right)} \tag{15}$$

The exponentiated forms of (14) and (15) thus yield the conditional expected value of PV_j, and (1) is finally used to compute IV_k.

D Patent value distributions by groups

Table D1: Distribution of applications' expected values by selected characteristics

Application group:	EP/EP-PCT & national phase	USPTO patents	National patents	All groups
25th percentile	7,701	2,742	442	4,016
50th percentile	105,612	5,868	796	43,502
75th percentile	595,511	92,087	61,494	324,382
90th percentile	2,214,025	362,617	185,663	1,553,453
95th percentile	4,597,177	1,771,236	312,654	3,127,839
99th percentile	17,811,804	3,697,271	903,464	12,873,817
Mean	1,072,812	227,622	66,459	743,470

Inventor's team size:	1	2 to 5	6 to 10	10 and above
25th percentile	3,618	3,715	4,596	6,366
50th percentile	29,355	26,519	50,068	99,189
75th percentile	244,084	237,773	399,634	709,494
90th percentile	1,322,444	1,173,256	1,712,088	2,385,999
95th percentile	2,714,229	2,600,351	3,609,480	4,243,329
99th percentile	10,376,591	9,782,558	14,572,037	14,876,156
Mean	627,288	620,253	870,174	1,001,960

Patent stock at appl. date:	0 (1th appl.)	1 to 9	10 to 24	25 and above
25th percentile	7,748	3,918	3,874	3,747
50th percentile	115,583	49,971	38,596	15,427
75th percentile	1,171,299	412,204	275,900	144,730
90th percentile	4,419,546	1,993,751	1,151,024	578,292
95th percentile	9,870,436	3,998,754	2,269,362	1,253,315
99th percentile	34,791,584	13,958,974	5,422,658	3,450,510
Mean	2,020,290	875,834	441,872	252,288

Start-up macro-region:	DACH	NORDICS	FR&BENELUX	SOUTH/CESEE	BI	ROW
25th percentile	4,149	4,754	4,549	5,258	3,142	5,080
50th percentile	46,304	51,781	46,964	172,021	25,074	48,479
75th percentile	408,824	677,149	363,363	923,895	184,968	315,757
90th percentile	1,621,066	2,732,952	1,536,450	3,037,310	912,311	1,813,381
95th percentile	2,997,827	6,852,340	3,285,323	7,277,147	2,319,639	3,262,570
99th percentile	13,345,709	26,792,904	11,057,323	40,143,292	8,325,731	7,683,510
Mean	788,680	1,350,261	727,519	1,813,538	543,666	632,707

Technology field:	ICT	Electronics	Life sciences	Other/Missing
25th percentile	3,724	3,849	4,499	3,895
50th percentile	42,843	45,810	43,977	40,368
75th percentile	255,499	239,552	435,684	270,597
90th percentile	1,207,069	1,082,792	1,893,771	1,343,101
95th percentile	2,638,932	2,503,667	3,755,912	2,867,373
99th percentile	7,977,006	6,819,948	16,310,921	14,562,696
Mean	540,118	510,490	918,184	735,278

All values in 2005 EUR. Sample sizes discussed in section 4.2.

E Further considerations on the skewness of patent value estimates

As discussed in section 4.4.1, while our value estimates are in line with the relevant literature, they also show a significantly higher skewness. To further substantiate this claim, we exploit the properties of the lognormal distribution and, based on the distribution moments reported in Table 9, we estimate the *Gini coefficient* to assess the rate of inequality among patent values.[39] Such *empirical* Gini coefficient relies heavily on the assumption that patent values in each study are *i.i.d* following a lognormal distribution.

Table E1: Comparison of estimated patent values (see Table 9 for sample details of each study)

Study	μ	σ	Skewness index	Gini index
Pakes (1986)	8.08	1.78	121.1	79.11%
Pakes (1986)	8.97	1.38	20.7	67.03%
Schankerman and Pakes (1986)	7.30	2.03	496.5	84.89%
Schankerman and Pakes (1986)	8.29	1.62	57.7	74.93%
Schankerman and Pakes (1986)	9.22	1.52	35.6	71.60%
Lanjouw (1998)	9.47	1.04	6.9	53.66%
Koléda (2005)	8.10	1.66	68.6	76.00%
Serrano (2005)	10.06	1.51	34.4	71.33%
Deng (2007)	10.45	2.52	13,740.8	92.52%
Bessen (2008)	8.96	2.19	1,309.3	87.77%
Bessen (2008)	11.12	2.77	101,402.9	95.00%
Bessen (2008)	9.79	1.94	293.4	83.00%
Bessen (2008)	10.89	1.11	8.3	56.55%
Bessen (2008)	9.94	2.18	1,255.1	87.66%
Grönqvist (2009)	7.43	1.69	78.5	76.79%
Gupeng and Xiangdong (2012)	7.50	2.28	2,539.8	89.38%
Gambardella *et al.* (2008)	12.85	2.12	836.4	86.53%
This working paper	6.68	2.97	582,124.1	96.46%
This working paper	11.57	2.15	1,063.3	87.21%
This working paper	8.68	2.70	58,425.8	94.42%

Note: studies may contain several estimation samples. Rows are ranked as in Table 9, containing further sample details.

We find our estimates to hold among the highest concentration rates, with a Gini coefficient comprised between 87.21% and 96.46%. For a reference, the Gini coefficient in Bessen (2008) ranges between 56.55% (for listed companies) and 95.00% (for foreign companies without constrained δ). The least dispersed distribution is found in Lanjouw (1998), with a coefficient of 53.66%.

Multiple causes may explain the increased concentration. First, our study pools granted and non-granted patents: comparing the Gini index of other studies we note a 3% average increase in studies that account for non-granted patents. Second, the geographical and temporal features of our sample are also likely to affect the distribution of estimated values.

However, it is the exclusive presence of young innovative start-ups that we consider key in explaining the higher Gini index. According to this view, the increased disparity of patent values originates in the higher risk profile of start-ups. We find some preliminary evidence of this conjecture in Bessen (2008), the only study to compare estimates between listed and non-listed companies (Gini index of 56.55% and 87.66% respectively).

[39] The parameter μ is computed as the log of the estimated median patent value. The standard error σ is computed as $\sqrt{2 * (\ln(\text{mean}) - \ln(\text{median}))}$. The remaining columns follow the methodology outlined in Aitchison and Brown (1957).

F Innovation values by start-up type

Figure F1: Innovation value classes by macro-region

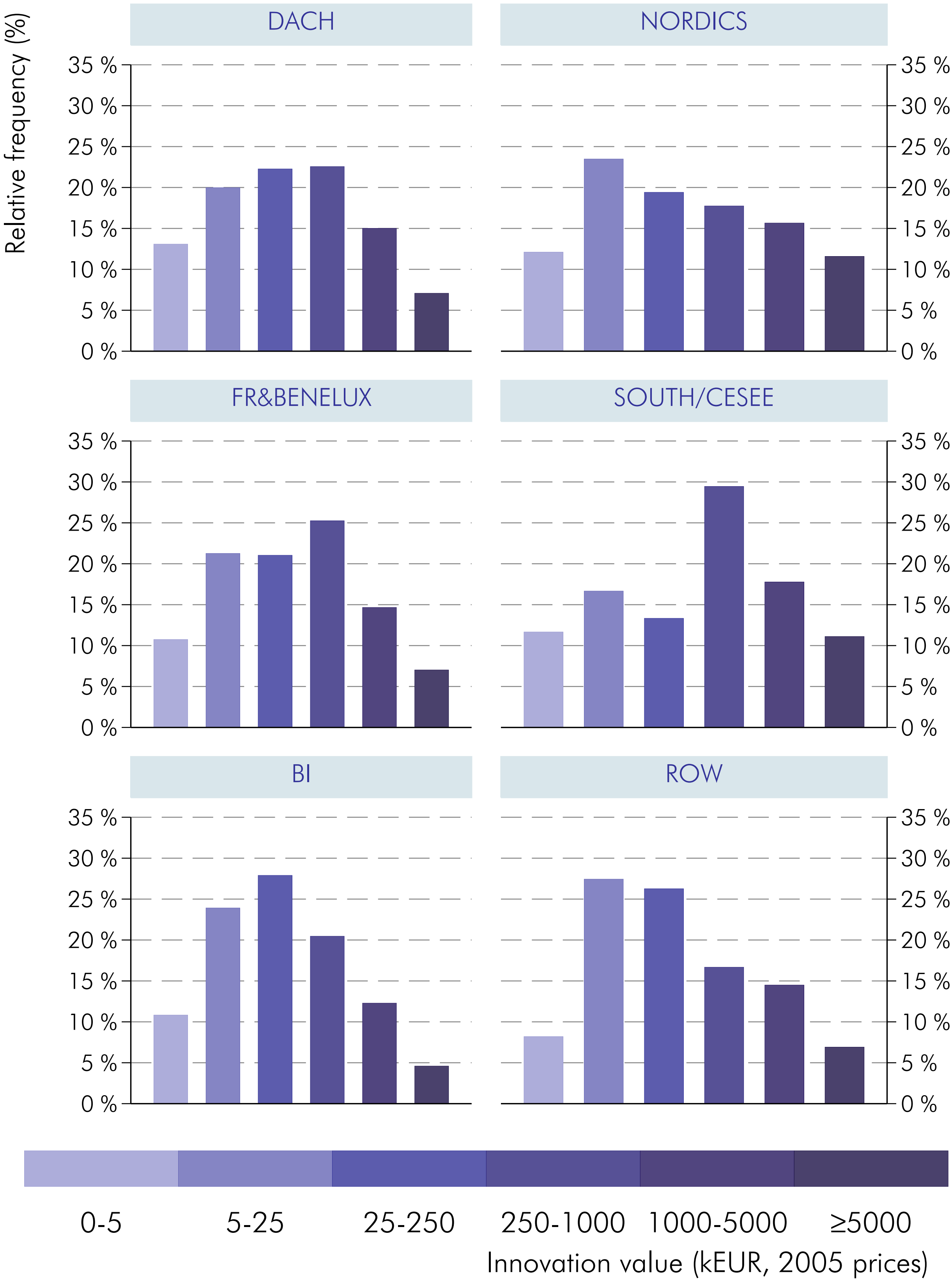

Figure F2: Innovation value classes by macro-sector

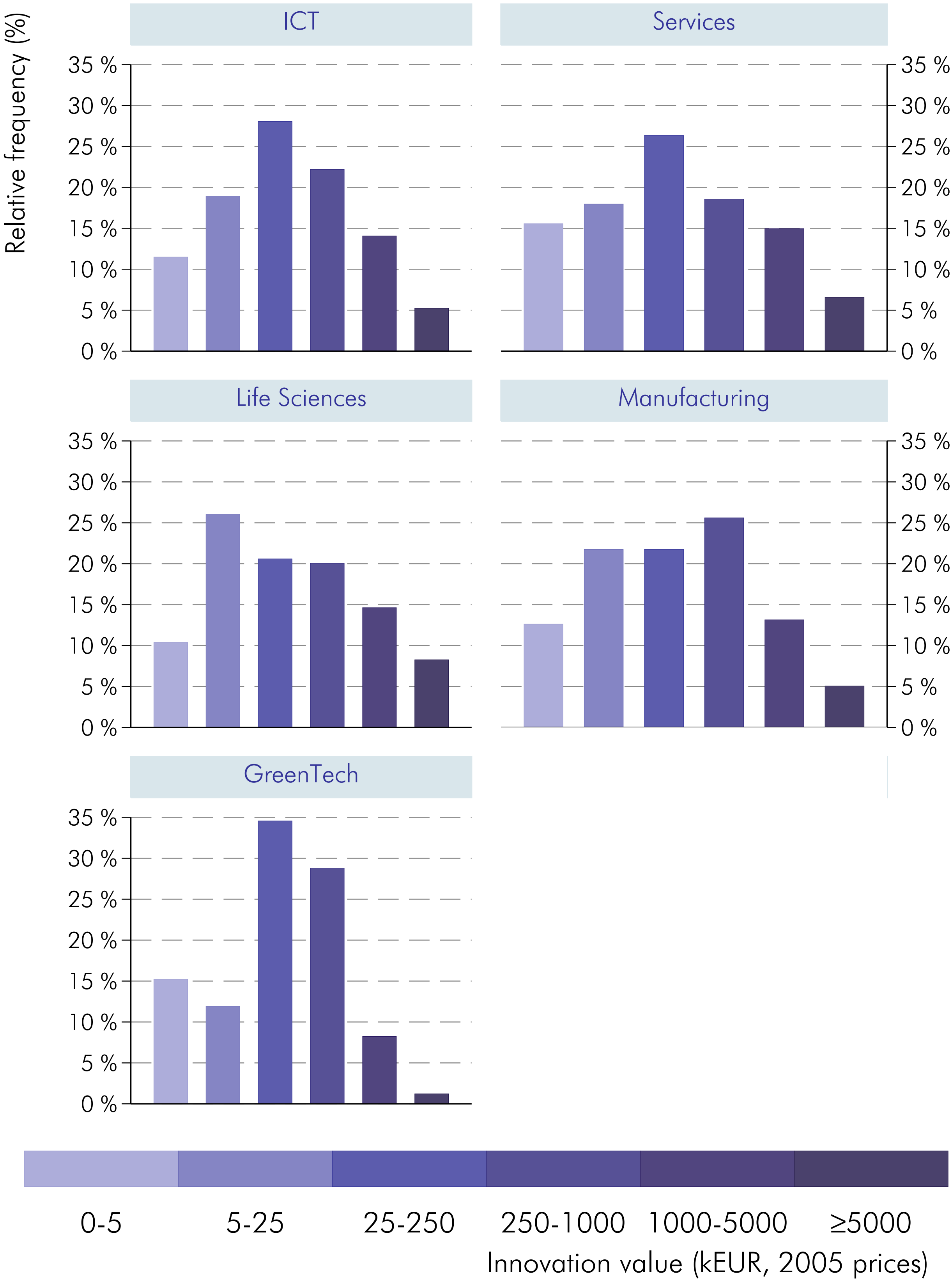

Figure F3: Innovation value classes by investment date (left) and age at investment (right)

G Factors affecting selection bias

Table G1: Dep. variable: % of applications with data per patent family (1–2) and start-up (3–4).

	Patent family[a]		Start-up[b]	
	(1)	(2)	(3)	(4)
	OLS	GLM[c]	OLS	GLM[c]
Citations received	-0.0002**	-0.0002**		
	(0.000)	(0.000)		
Number of inventors	-0.0053***	-0.0061***		
	(0.000)	(0.001)		
PO concentration (HHI)[d]	0.0462***	0.0897***	-0.0216	-0.0125
	(0.005)	(0.013)	(0.021)	(0.024)
Log. of first investment amount			-0.0051	-0.0036
			(0.003)	(0.002)
Geographic macro-region: *(baseline: DACH)*				
NORDICS	-0.4004***	-0.4929***	-0.1810***	-0.1668***
	(0.011)	(0.019)	(0.021)	(0.027)
FR&BENELUX	0.0055	0.0011	-0.0331*	-0.0276**
	(0.008)	(0.013)	(0.018)	(0.014)
SOUTH/CESEE	-0.5272***	-0.6075***	-0.1034***	-0.0894***
	(0.015)	(0.021)	(0.032)	(0.033)
BI	0.0310***	0.0414***	-0.0187	-0.0151
	(0.007)	(0.010)	(0.017)	(0.012)
ROW	-0.0331***	-0.0680***	-0.0340	-0.0280*
	(0.008)	(0.013)	(0.023)	(0.017)
EPO (only patent families)	-0.0250***	-0.0404***		
	(0.007)	(0.009)		
Technology field: *(baseline: ICT)*				
Life Sciences	-0.0094*	-0.0131*	-0.0246*	-0.0195**
	(0.005)	(0.008)	(0.013)	(0.009)
Electronics	0.0085	0.0152		
	(0.006)	(0.009)		
Other/Missing	0.0360***	0.0466***	-0.0419**	-0.0296
	(0.007)	(0.013)	(0.020)	(0.019)
Reference period:[e] *(baseline: pre-2001)*				
from 2001 to 2007	0.0279***	0.0489***	0.0182	0.0106
	(0.006)	(0.010)	(0.015)	(0.011)
from 2007 to 2015	-0.0586***	-0.0821***	-0.0483***	-0.0396***
	(0.006)	(0.011)	(0.017)	(0.015)
Application stage: *(baseline: Application)*				
Publication	0.1026***	0.1091***		
	(0.010)	(0.019)		
Examination	0.1077***	0.1110***		
	(0.009)	(0.019)		
Grant	0.0342***	0.0414**		
	(0.010)	(0.018)		
Reissue	0.0980***	0.1163***		
	(0.013)	(0.020)		
N° of observations	12,675	12,675	997	997
(Pseudo) R-squared	0.25	0.17	0.12	0.05

* $p<0.05$, ** $p<0.01$, *** $p<0.001$; [a] Explanatory variables aggregated at patent family level as follows: *maximum* for continuous variables, *mode* for technology field and geographic location, *latest status* for application stage;
[b] Uses only company-level explanatory variables; [c] Average marginal effects shown;
[d] Measures the patent office concentration among patent families in models (1) and (2), and companies in models (3) and (4) by means of the Herfindahl-Hirschman index; [e] *Reference period* indicates the application year for models (1) and (2), and the period of first EIF-backed investment for models (3) and (4).

H Innovation timing and value

Table H1: Determinants of innovation value (Dep. variable: *log* of innovation value in 2005 EUR)

Variable	OLS[a]	OLS (1st innov. only)[a]	Quantile regression[b] 25th quantile	50th quantile	75th quantile
Submission date ('00 days to/since inv. date)	-0.0404*** (0.004)	-0.1025*** (0.007)	-0.0134*** (0.002)	-0.0384*** (0.003)	-0.0554*** (0.002)
Initial innovation[†]	0.7415*** (0.114)		0.8382*** (0.289)	0.7965*** (0.128)	0.7001*** (0.086)
ln (Investment amount)	0.0671** (0.030)	0.1456*** (0.056)	0.0708*** (0.022)	0.0858*** (0.025)	0.0262 (0.018)
Start-ups' age at founding	0.0098 (0.033)	-0.0142 (0.043)	0.0227 (0.016)	-0.0049 (0.023)	0.0214* (0.013)
Start-up industry: *(baseline: Life sciences)*					
ICT	0.0276 (0.140)	-0.7643*** (0.211)	0.0680 (0.062)	0.3463*** (0.093)	-0.0634 (0.053)
GreenTech	-0.1544 (0.200)	-0.4504 (0.419)	-0.0096 (0.114)	-0.0753 (0.167)	-0.1934** (0.091)
Services	-0.7593*** (0.254)	-1.1825** (0.575)	-0.3489 (0.288)	-0.8264** (0.410)	-0.7558*** (0.206)
Manufacturing	-0.6006 (0.388)	-0.0921 (0.426)	-0.1798 (0.433)	-0.4557** (0.201)	-0.4995*** (0.119)
Geographic macro-region: *(baseline: ISL)*					
DACH	0.2562 (0.173)	-0.2291 (0.269)	0.0698 (0.064)	0.4380*** (0.105)	0.2972*** (0.065)
NORDICS	0.3207 (0.203)	0.0258 (0.305)	-0.0561 (0.083)	0.1124 (0.166)	0.5005*** (0.107)
FR&BENELUX	0.5433*** (0.160)	0.8981*** (0.259)	0.2364*** (0.087)	0.7182*** (0.110)	0.5936*** (0.062)
SOUTH/CESEE	0.7516 (0.480)	0.3478 (0.443)	0.0728 (0.376)	1.3571*** (0.364)	0.8680*** (0.154)
ROW	0.2486 (0.236)	0.1646 (0.299)	0.1669** (0.069)	-0.0388 (0.130)	0.2806*** (0.078)
Reference period: *(baseline: pre-2001)*					
2002-2007	-0.2795** (0.133)	-0.7648*** (0.204)	-0.0102 (0.054)	-0.1312 (0.097)	-0.7606*** (0.056)
2008-2014	-0.4354** (0.214)	-1.6720*** (0.251)	1.3447*** (0.388)	0.0438 (0.143)	-1.4991*** (0.092)
Constant	3.9039*** (0.450)	4.1583*** (0.876)	1.2282*** (0.355)	3.7362*** (0.407)	6.9075*** (0.293)
Nr. of observations	11,597	929	11,597	11,597	11,597
R^2	0.07	0.24	0.01	0.03	0.08

[†] dichotomic variable; [a] Firm-level clustered standard errors; [b] Bootstrapped standard errors (500 replications).

I List of acronyms

- API: Application Program Interface
- CIS: Community Innovation Survey (Eurostat)
- DOCDB: DOCument DataBase (information system)
- ECB: European Central Bank
- EP/PCT: European Patents under the Patent Cooperation Treaty
- EPC: European Patent Convention
- EPO: European Patent Office
- EU: European Union
- GDP: Gross Domestic Product
- GLM: Generalised Linear Model
- ICT: Information and communication technology
- INPADOC: International Patent Documentation (international patent collection system)
- IP: Intellectual Property
- IPC: International Patent Classification
- MLE: Maximum Likelihood Estimation
- OLS: Ordinary Least Squares
- PATSTAT: Patent Statistics (EPO's worldwide patent statistic database)
- PCT: Patent Cooperation Treaty
- PO: Patent Office
- R&D: Research and Development
- RAKE: Rapid Automatic Keyword Extraction
- SME: Small and Medium-sized Enterprise
- USPTO: United States Patent and Trademark Office
- VC: Venture capital
- WIPO: World Intellectual Property Organization

List of geographic macro-regions:

- BI (British Isles): United Kingdom, Ireland
- CESEE (Central Eastern and South-Eastern Europe): Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, Slovenia, Slovakia, Turkey
- DACH: Germany, Austria and Switzerland
- FR&BENELUX: France, Belgium, Netherlands, Luxembourg
- N-AM: United States, Canada
- NORDICS: Denmark, Finland, Norway, Sweden
- SOUTH: Greece, Italy, Malta, Portugal, Spain
- ROW: Rest of the World

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