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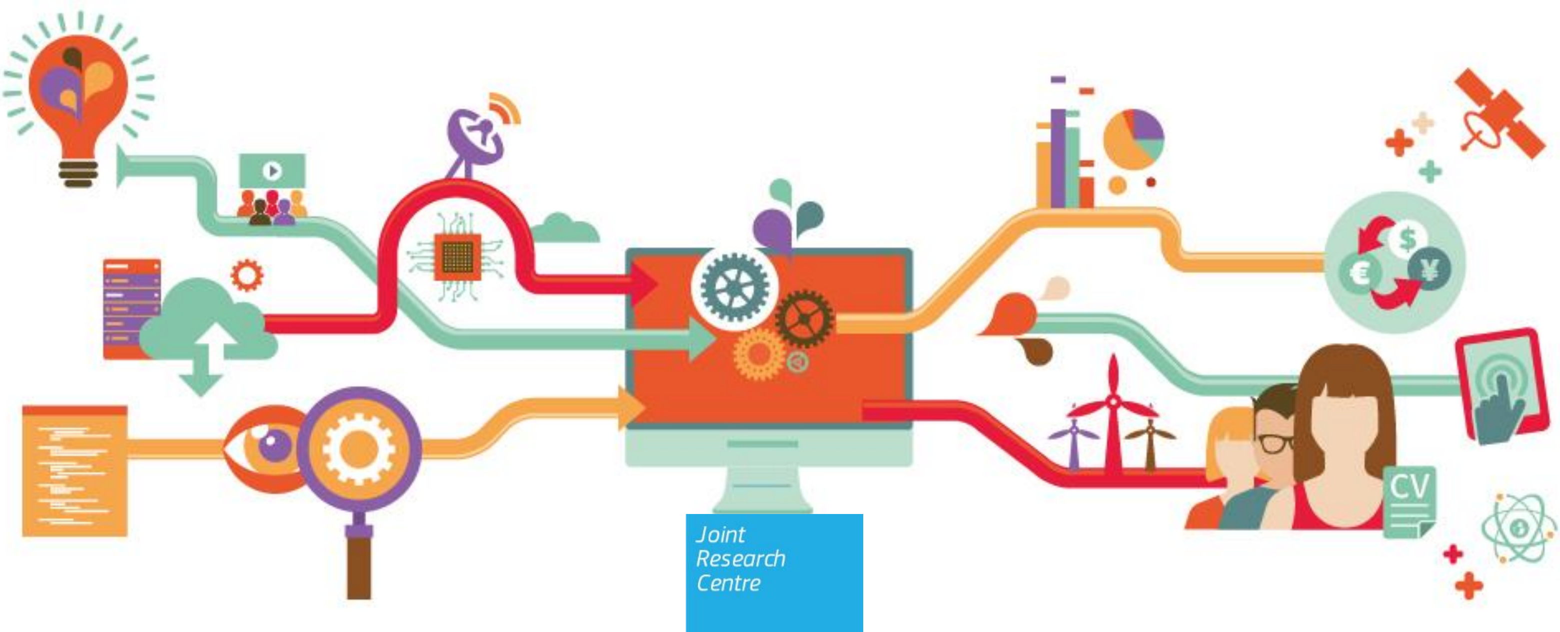

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Heterogeneity of technology-specific R&D investments. Evidence from top R&D investors worldwide[1]

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Abstract

In this work, we develop and apply a methodology to estimate technology-specific R&D investments at the firm level and then use these to test some arguments that have become central in the innovation literature. In particular, we first combine R&D investments with patent data of the world top R&D investors worldwide and show that investment per patent varies greatly both across technologies and across firms developing the same technology. We then use the estimated firm-technology R&D investments to assess how these are related to the international and technological strategies of firms. The estimation strategy makes use of a multilevel framework that allows us to model heterogeneity both at the firm and industry level. In particular, we show that specific firms strategies requires different level of investments and that sector specificities matter in determining R&D per patent investments, economies of scale in knowledge production, and the cost of (further) specialization. Accounting for (un)observed heterogeneity may lead to better policy design and management decisions.

Keywords: patents; R&D; technology; cost; heterogeneity; internationalization.

JEL Classification: O3, O14; L10; D23

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1. Introduction

R&D and innovation are key components of firm competitiveness and long term growth. However, the potential gap between private and social returns to innovation may lead to underinvestment in R&D (Arrow, 1962). Actually this underinvestment seems to be severe, with companies investing about half of the socially optimal level (Bloom et al., 2013). It has been argued that to incentivize R&D investments firms should be granted, to a certain degree, with monopoly rights to allow them protecting their innovations from imitation and recover the associated R&D investments. Patents are a devise to grant monopoly rights, for a specific period of time, to firms and individuals for innovations that can be considered as truly new (novelty requirement). Moreover, patents - made public 18 months after filing - provide a wealth of information on the technological, geographical and qualitative dimensions of the protected invention (Pavitt, 1985; Griliches, 1990; Hall and Harhoff, 2012).

The relationship between R&D and patents – the so called propensity to patent (Scherer, 1983) - has been widely investigated in the field of economics of innovation and differences across industries and firms of different size have been observed. However, the difficulty of assigning R&D investments to patents and specific technologies on a systematic basis drove the attention to the analysis to the value of patents. There have been basically two approaches to derive indicators of value: i) building quality measures from patent documents to proxy different dimensions of value; ii) trying to infer the (private) economic value of patents from firms' data. Recently, Squicciarini et al. (2013) provided a large compendium of measures of patent quality following the former approach, while the paper of Kogan et al. (2017) represents instead an example of the latter. In their work, these authors build a measure of patent economic value by trying to assess the present value of the monopoly rents associated with a patent from stock evaluation data. Both approaches are more focused on assessing the value of an invention for a given firm rather than trying to assess the effort made by the same firm to get this invention. In principle, firms may get higher than the average returns for their inventions irrespective of their investment efforts, thus these results may be scarcely informative about a possible underinvestment in R&D.

In this contribution we try to go back to the roots and estimate the R&D investment associated with patents pertaining to specific technologies. In other words, we look back at the "investment side" of the economic dimension of patents to assess its heterogeneity across technologies, firms and industries. In addition, we use the technology-specific R&D investment to test some arguments that have become central in the innovation literature in recent years, attracting also increasing interest from the policy community. More specifically, we will look at the relationship between a firm's technology-specific R&D investment and its technological and international knowledge production strategies.

Indeed, globalization of firms activities attracts a lot of attention by scholars and policy makers, which moved their focus from the delocalization of low-end productive activities to the internationalisation of most knowledge intensive (R&D and innovation) ones. However, despite the great interest, the magnitude and specificities of this phenomenon are still far from being completely understood. The increasing availability of patent data, and the information on applicants' and inventors' residence, allows for a better description of the internationalization of innovative activities (Picci, 2010; Gkotsis and Vezzani, 2016; Awate and Mudambi, 2017). We will leverage these possibilities to assess the extent to which internationalisation of knowledge activities may require additional investment that firms should take into account along with the potential benefits. The geographical dimension of innovative activities add to a well consolidated body of literature, dating back to the seminal contribution of Griliches (1979), on the nexus between R&D and productivity and on the use of the informative value of patents to proxy the firm's capacity of transforming R&D into economically valuable knowledge. In addition, we will also assess the importance of firms' technological strategies, their degree of specialisation, their technological breadth and the degree of competition in a specific technology market, in (co)determining technology-specific R&D investments.

In the following, we combine R&D investments with patent data of the world top R&D investors (Guevara et al., 2015) to derive technology-specific investment vectors. By doing so, we uncover the high heterogeneity underlying the technology-specific R&D investment both across firms and industries. We will then use the estimated investment vectors in a multilevel regression framework to test the relationship between a firm's technology-specific R&D investment and its technological and international knowledge strategies.

2. Motivation and framework

The main aim of this paper is twofold: estimating technology-specific patent R&D investment and using them to look at some relationships discussed in the innovation literature. As such, the paper has a double nature. On the one hand, it proposes a methodology to estimate technology-specific R&D investment that allows taking into account the heterogeneity underlying the patent-investment relationship. On the other hand, it looks at the relationship between technology-specific R&D investment at the firm level and the characteristics of the firm's innovation strategy, as well as the degree of development of the technology in the market.

Estimating technology-specific R&D investments is not easy and previous attempts have mainly focused on specific subsets of homogeneous technologies; see for example Wiesenthal *et al.* (2012) or Breyer *et al.* (2013) for the case of technologies related to energy production. In these cases, where firms are highly specialised and with technologically narrow patent portfolios, it is relatively safe to directly associate patents to research and development investment. Here, we exploit a sample of top R&D investors worldwide to estimate R&D investments for the full set of technological fields linked to patent documents and to assess differences amongst them. Addressing this issue has always been difficult due the lack of detailed company data. In this respect, the EU Industrial R&D Investment Scoreboard (Guevara *et al.*, 2015) is a particularly suitable source of data, as it provides R&D data of the world top corporate R&D investors, for which the corporate structure can be used to fully track their patenting activity. Most of these companies are multinational industrial groups operating in diverse markets and dealing with a diversified portfolio of technologies.

Indeed, the wide set of technologies considered in the analysis and the different industries in which the companies of our sample operate, pose challenges in estimating the right vector of associated R&D investments. For this reason, we draw from the methodology proposed by Fiorini *et al.* (2016) to build a vector of technology-specific investment by averaging sample figures and then use this vector as a starting point in the search for firm specific investments. Feeding the optimization algorithm(s) with reasonable initial conditions reduces the search space and provides more stable results. Indeed, we look for firms' specific solutions to model heterogeneity and the use of the initial vector of average R&D investment helps finding solutions with the property of being relatively close to the overall picture (e.g. reducing the probability of extreme deviations). In a recent report, Dernis *et al.* (2015) showed that the patent propensity (R&D investment per patent) varies within and between sectors, as well as the technological portfolios of firms. Here we want to go a step further and address technology specificities; we believe this is a necessary step to better understand firms' innovation strategies and provide guidance for policy makers.

Regarding firm innovation strategies, Quintana *et al.* (2008) showed how a diversified technology base positively affects firms' innovative capabilities, with a particular effect on exploratory rather than on exploitative activities (March, 1991). Belderbos *et al.* (2010), looking at the firm financial performance related to the two types of innovative activities, argued that this is maximised by a combination of the two, rather than a specialization in only one of them. More recently, Neuhäusler *et al.* (2016) analysed the link between firms' technological bases and financial performance, arguing that a higher technological *breadth* can serve as a hedge against technological and commercialization risks. This may be linked to the fact that technology *breadth* can be seen both as an indicator of knowledge integration and of technological diffusion (Hu and Rousseau, 2015). All-in-all, technological *breadth* seems to matter for firms' competitiveness. However, it is not clear if a higher technological *breadth* also entails higher R&D investments or whether these rather increase with specialisation. Again, the link between increasing returns and specialisation (Romer, 1987) gives us insights from the output, but not from the input side. Moreover, the competition by other firms actively developing a specific technology is also a crucial factor defining and shaping a firm's knowledge production strategies. Indeed, competition affects the cost and effort required to develop technologies and products in line with those of competitors (Almeida, 1997; Christensen, 2013).

The increased integration of economic activities and the raising of the knowledge economy brought forward the importance of the global dimension of innovation

(Archibugi and Iammarino, 2002). Companies, multinational corporations in particular, increasingly locate research facilities abroad. Their international strategies are mainly driven by the objective of tapping into new knowledge and capabilities complementing their in-house technological activities (Chung and Alcácer, 2002; Cantwell *et al.* 2004; Criscuolo *et al.* 2005). However, in their search firms are bounded by the path-dependent and cumulative nature of the innovation process (Dosi 1988); suggesting that international knowledge seeking strategies should reveal a certain degree of technological proximity between the in-house activities and those of the targeted countries (Dosso and Vezzani, 2015). Internationalization (or multinationality) can exert different effects depending on its *depth* - the share of the multinational activities - and its *breadth* - the geographical dispersion of the multinational activities (Contractor *et al.*, 2010). International *depth* measures the intensity of the recourse to international knowledge markets which may be related to the firm's capacity to establish and maintain long lasting relations within the international research context, thus increasing its potential of gaining from knowledge externalities (Katila and Ahuja, 2002). The international *breadth* of innovative activities may indeed offer firms the possibility of accessing and combining ideas from different contexts (Hitt *et al.*, 1997; Cantwell and Mudambi, 2005) thus increasing the probability of finding new valuable discoveries (Kafouros *et al.*, 2012). In both cases, international knowledge seeking entails costs which may be eventually (more than) covered by the increasing returns to scale in R&D (Cohen and Klepper, 1996). This may explain why, among multinational companies with highly internationalised activities those investing more in R&D are the ones possibly benefiting most from internationalisation (Castellani *et al.*, 2017).

Given the prominent role of the technological and international dimensions in the current debate about the factors shaping firms' performances; in the second part of the empirical application we will use the estimates of technology-specific R&D investments to test the direction and strength of these factors in determining the overall R&D investments of a firm. In particular, we proxy the technological *breadth* of a firm by the number of technological fields covered by its patent portfolio and its specialisation as the share of its patents in a given technological field.[2] Similarly, we will proxy international *depth* as the share of patents involving at least an inventor residing in a country different from that where the headquarters is located and international *breadth* by the number of countries in which inventors of a given firms reside. Finally, to proxy technological competition, we will consider the number of companies with patenting activity in a given technological field.

[2] In our framework, the use of the simple patent share to proxy specialisation (and the implied investments) seems more appropriate than other measures of specialisation more frequently used in the literature as the revealed technological advantages, which are comparative in nature. However, in the empirical application we will show that our results hold true both when considering shares and SRTAs (we will come back on SRTA later on).

3. Data and methodology

3.1 Data

Patents are the main output of technology-oriented R&D activities. They contain useful information about the invention, such as the technical fields to which the patent pertains and the addresses of the different actors in the innovation process (applicants and inventors). Patent documents are classified into technical fields based on a hierarchical classification system, the International Patent Classification system (IPC) which has been mapped into 35 technological fields by WIPO (WIPO, 2013) in order to allow for comparisons between countries and industries, and analyse technological development.

The empirical application is based on the top 2000 R&D investors worldwide as reported in the 2015 edition of the EU Industrial R&D Scoreboard (Guevara *et al.*, 2015). From the EU Industrial R&D Scoreboard we retrieve information on firms' R&D investments for the 2012-2014 period, their industrial classification and the location of the headquarters. From the Orbis database (Bureau van Dijk), we obtain information on the subsidiary structure of our firms in 2014; this is then used to retrieve their patent portfolios from the Worldwide Patent Statistical Database (PATSTAT)[3], 2016B edition. The link between the two databases makes use of a series of probabilistic string matching algorithms (IMALINKER)[4] and is carried out on a country-by-country basis. The final sample consists of 1719 Scoreboard companies having filed patents at the five top Intellectual Property Offices (EPO, JPO, KIPO, SIPO, USPTO) in the 2012-2014 period. These companies are linked with about 356,600 distinct patent documents, which correspond to 177,979 unique INPADOC families,[5] with at least one patent document filed in one of these offices plus another linked document anywhere in the world; the IP5 families (see Dernis *et al.*, 2015). The choice of using patents from the major patent offices worldwide (which mirror the main technological markets) protect us from the so called home-bias (Dernis and Khan, 2004) guaranteeing a balanced representation of the patent portfolios' of firms from different countries.

3.2 Estimating technology-specific patent investment

The estimation of technology specific R&D investment per patent could be done either through weighted averages (Fiorini *et al.*, 2016) or by attempting to solve an optimization problem where, for example, R&D is distributed across technologies in order to minimize the total sum of residuals (generally squared or in absolute terms).

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[3] PATSTAT is the European Patent Office's Worldwide Patent Statistical Database, which contains data on about 70 million applications from more than 80 countries. See http://www.epo.org

[4] Idener Multi Algorithm Linker developed for the OECD by IDENER, Seville, 2013

[5] Companies may seek protection for their invention at different world regions by filing patent applications at different Intellectual Property Offices (IPOs). In order to control for the multiple filing of the same invention at different IPOs, different patent applications have been matched through INPADOC (International Patent Documentation) families to avoid double counting see http://www.epo.org/searching/essentials/patent-families/inpadoc.html.

The main constrain of these approaches is that they provide a unique vector of technology-specific values, equal for all companies. Heterogeneity across firms is not allowed, meaning that all firms share the same 'knowledge production function'; a plausible assumption only when specific industries or technologies are the object of the study.

In order to overcome these limitations we combine the two approaches by first computing a vector of technology-specific investment as the sample weighted average and then feeding it as initial value of a minimization algorithm to parametrize technology investment at the firm level. This allows us to model the distribution of investments across firms.

3.2.1 Averaging technology R&D investment

Following Fiorini *et al.* (2016), we aggregate company level information in order to estimate the average R&D investment associated with the development of a patent in a specific technological field.

In order to do so, we first fractionally count the number of patent families of each firm across technological fields (P_i^j), as the number of patent families filed by firm i, pertaining to a given technological field j during the 2012-2014 period.[6] Patents covering different technological fields are split among them; for example, if a patent covers three technological fields it is split among the three fields according to the number of codes belonging to each field. The total number of families owned by firm i (P_i), can be computed as:

$$P_i = \sum_{j=1}^{35} P_i^j \tag{1}$$

The total R&D investment for the 2012-2014 period of a firm (RD_i) is then allocated across the 35 technological fields according to the relative share of patents in the firm portfolio:

$$C_i^j = \frac{P_i^j}{P_i} \times RD_i \tag{2}$$

In deriving equation 2 the implicit assumption is that, within a firm, the investment required for developing a patent is homogeneous across technological fields. The average investment per patent related to a specific technological field $\overline{C^j}$ is then calculated as the total amount of R&D spent for developing patents in this specific field

[6] A significant effect of R&D on patenting, operating within a year lag, and the fact that different projects (of different duration and scope) co-exist within companies have been largely documented. These two facts may introduce noise in the search of technology-specific R&D investments. By averaging data over three years we hope to better describe the technological innovation set of companies (David *et al.*, 2000) and increase the signal to noise ratio in the data.

by the firms of our sample $\sum_i C_i^j$ divided by the total number of patent families in the same field owned by these firms $\sum_i P_i^j$:

$$\overline{C^j} = \frac{\sum_i C_i^j}{\sum_i P_i^j} \tag{3}$$

This vector is unique across the sample, which means that technology associated investments are equal for all companies. In the following, we will use this vector as an initial condition to estimate firm's specific R&D investment and relax the two assumptions discussed above.

3.2.2 Estimating technology R&D investments per patent

Let $\overline{C^j}$ be the average R&D investment per patent for technical field j (see Table A.1 in the appendix). Then for each company i with total R&D investment RD_i and P_i^j patent families in the technological field j, the following equation would hold true only when the distribution of patents across technological fields of a firm is identical to that of the overall sample:

$$RD_i = \sum_{j=1}^{35} P_i^j \times \overline{C^j} \tag{4}$$

In practice the equality in (4) never holds true. We therefore introduce a set of continuous positive parameters λ_{ij} to account for the fact that the investment required to develop a patentable invention in a specific field might vary across different firms; in other words we model the heterogeneity in the knowledge production of firms through the distribution of λ_{ij}. This way the parameters λ_{ij} "adjust" the weighted sample average investment $\overline{C^j}$ calculated previously to obtain firm-technology specific investment: $C_i^j = \lambda_{ij}\overline{C^j}$.

In matrix notation, equation (4) becomes:

$$RD_{n\times 1} = (P_{n\times m} \circ \Lambda_{n\times m}) \cdot C_{mx1} \tag{5}$$

where n stands for the number of firms and m the number of technological fields. The matrix multiplication between P and Λ is performed on an element by element basis: the result is the Hadamard product, which is also a matrix with n rows and m columns. C is a column vector with entries corresponding to the 35 weighted sample average investment $\overline{C^j}$ derived previously.

In order to solve the optimization problem and estimate the λ_{ij} parameters, we minimize the following objective function:

$$\min_m \| RD_{n\times 1} - (P_{n\times m} \circ \Lambda_{n\times m}) \cdot C_{mx1} \| \tag{6}$$

under the following constraints:

$$\Lambda_{ij} > \vec{0} \tag{7}$$

$$\text{and } \Lambda_{ij} = 0 \text{ if } P_{ij} = 0 \tag{8}$$

Formulas 7 and 8 express mathematically the obvious constrains that investments should always be a positive number if company i holds patents in field j and equal to zero if not (in which case the corresponding ij entry in matrix P is also 0). In order to obtain an optimal solution for the elements of matrix Λ under the constraints 7, 8 we use a genetic algorithm implemented with Matlab®. Genetic algorithms (GA) belong to a broader class of population-based optimization algorithms inspired by the principles of natural evolution which are called evolutionary algorithms. More specifically starting from an initial set of solutions, built around our initial condition, the algorithm modifies it in each iteration (generation) by selecting those solutions according to equation 6 (the fitness function), to serve as parents for the subsequent iteration. During the "reproduction process" solutions undergo random changes as a result of different mechanisms such as mutation and crossover.[7] We have solved the optimization problem both by building the initial set of solutions randomly and by setting the λ_{ij} parameters equal to 1 (that implies assuming that the investment per patent across firms are homogeneous), and let the population of solutions for each iteration varying between 50 and 100; results are robust to the different settings. In the following we will present the results where the initial condition implies homogeneity. Moreover, to estimate the lambda parameters we have filtered out companies with less than 5 patent families per year; this allows us to reduce the noise that may be caused from companies showing very high R&D investment per patent due to the rather small number of filings.[8] Finally, while the objective function from equation 6 minimizes the sum of absolute values of the individual terms, we obtain quite similar results when we use the sum of squares instead.

3.3 Determinants of R&D investment: the estimation framework

In order to analyse the contribution of different factors in determining technology-specific R&D investments per patent, we use a linear mixed-effects model, also known as multilevel model. The choice is driven by the fact that we observe patent R&D investment per technology at the firm level; therefore our basic observations are clustered within firms, which in turn operate in different industries.

[7] Mutation, similarly to its biological counterpart, involves random changes of parts of the solutions (our counterpart for an individual). In crossover, parts of different parent solutions are mixed to generate a child solution from them.

[8] In any case, the filtering choice does not affect significantly the overall sample results presented in table 2.

Table 1: Data structure

$cost_{tech\_1}$		
…	$firm_a$	
$cost_{tech\_N}$		
$cost_{tech\_1}$		$industry_k$
…	$firm_b$	
$cost_{tech\_N}$		

In order to take into account the clustered structure of the data, the mixed approach allows for the estimation of intercepts parameters at the firm and industry level. In particular, we will estimate an equation of the form:

$$rd_{ij,k} = \beta_0 + \beta_1 Spec_{ij} + \beta_2 Pat_j + \beta_3 W_i + \delta Z_j + \theta + u_j + u_{1k} + u_{23,k}(Spec, Pat) + \epsilon_{ij,k}$$

where $rd_{ij,k}$ stands for the R&D investments in one of the technological classes defined by the WIPO classification (i = 1,…,35) made by firm j operating in sector k. In the estimation we include a number of variables that refer to different levels of observation. $Spec_{ij}$ is the share of patents a firm has in a given technology and measures its technological specialization; in addition, we also check the importance of relative specialisation of a firms in developing the specific technology. In particular, we estimate the model alternatively using as a measure of specialisation the revealed symmetric comparative advantage, RSCA (Laursen, 2015), computed at the sample and industry level.[9] Pat_{ij} is the (natural logarithm of the) patents filed by the company, a measure of its overall technical knowledge production (Griliches, 1990). W_i is a technology specific variable: the number of companies developing a given technology. This is meant to proxy the (potential) competition within a specific technology market. Z_j stands for a series of firm specific variables. Namely, we consider: *i)* the number of technological fields related to the patents filed by a company, a measure of the breadth of its technological knowledge; *ii)* the share of international patents filed by the company,[10] a measure of its international depth; *iii)* the number of foreign inventor countries, a measure of its international breadth. Moreover, θ represents a series of binary variables identifying the headquarter location of a company, u_j and u_k stand, respectively, for the firm and industry random

[9] The RCA of a firm in developing a technology is computed by dividing the share of its patent in the technology by the sample (and industry) average; values above 1 said that a firm is relatively specialised in developing the technology. Laursen (2015) shows that making the index symmetric, as (RCA – 1)/(RCA + 1), provides a better measure of comparative advantages.

[10] Similar to Picci (2010) we consider a patent as international if at least one of the inventors involved has a residence different from that of the headquarter location.

effects, and $\epsilon_{ij,k}$ is the error term. The terms u_j, u_k and $\epsilon_{ij,k}$ are assumed to be normally distributed and independent. The random terms, allow us to account for the heterogeneity of patenting strategies (or patent propensity) both at firm and at industry level. Finally, besides controlling for random industry and firm intercepts we also estimate industry specific random slopes through the terms $u_{2k}(Spec, Pat)$. The specific combination of technological opportunities, appropriability conditions, cumulativeness and properties of the knowledge base in an industry, the so called technological regimes (Breschi *et al.*, 2000), are likely to influence the relationship between specialisation and economies of scale in the knowledge production; the introduction of the random slopes allows us to explicitly model this (expected) heterogeneity.

4. Results

4.1 Technology specific R&D investment

In table 2, we report the estimated R&D investment per patent for the 35 WIPO technological fields together with their coefficient of variation across firms, skewness, kurtosis and the share of companies with patenting activity in the field. It is important noticing that not all inventions are patented and firms may opt for informal mechanisms to protect their innovations, such as secrecy, confidentiality agreements or lead time (Hall *et al.*, 2014).[11] This means that our estimates, as others, may somehow represent "high-bound" values. For this reason, we also include a column where technology specific investments are divided by the overall sample average. These relative values provide 'scale free' figures, allowing for a direct comparison of R&D investment across technologies.

Pharmaceuticals technologies appear to be the most expensive in terms of R&D investments per patent. At the other extreme, Textiles and Optics are among those requiring the lowest investment. The variability of the estimated technology costs across firms is in general relevant, with standard deviations larger than mean values. Furniture, games shows the highest coefficient of variation (1.9), while Computer technologies, Measurement and Electrical machinery, apparatus, energy are those where investment are more homogeneous across firms (coefficient of variation = 1.1).

The high values of (positive) skewness and kurtosis highlight the fact that R&D investments per technology are not normally distributed across firms. This is also hinted by the distributions of lambdas - reported in figure A.1 in the appendix – which are largely lying close to 1 with a mean lower than the median (positive skewness), but also exhibit rather fat tails (high kurtosis).

[11] However, this is also in part due to the fact that patented innovations should be novel and non-obvious, concern field of knowledge that are technological, and have industrial applicability or utility (OECD, 2009). Broadly speaking the last two criteria imply that aesthetic creations, laws of nature, abstract ideas and scientific inventions are not patentable.

Table 2: R&D investment by technology and their variation across companies

Technology field	Average	Coef. of variation	Skewness	Kurtosis	Share of companies developing	Relative investment
Pharmaceuticals	10.5	1.6	3.4	23.5	43%	3.5
Biotechnology	6.8	1.5	3.1	18.2	43%	2.3
Organic fine chemistry	5.9	1.4	2.7	17.1	44%	2.0
IT methods for management	5.5	1.5	2.9	15.0	45%	1.9
Transport	5.0	1.5	4.3	30.7	50%	1.7
Analysis of biological materials	4.5	1.5	2.3	10.6	39%	1.5
Computer technology	4.5	1.1	3.9	31.4	61%	1.5
Digital communication	3.6	1.4	3.2	19.9	49%	1.2
Measurement	3.4	1.1	3.7	25.9	62%	1.2
Mechanical elements	3.4	1.3	3.7	27.4	54%	1.1
Engines, pumps, turbines	3.0	1.5	3.6	22.8	49%	1.0
Other special machines	3.0	1.3	3.1	19.1	56%	1.0
Medical technology	2.8	1.3	3.4	28.6	49%	0.9
Control	2.7	1.2	3.2	24.0	54%	0.9
Chemical engineering	2.6	1.4	4.8	44.6	46%	0.9
Environmental technology	2.6	1.7	4.2	31.3	54%	0.9
Basic materials chemistry	2.6	1.3	2.8	16.7	50%	0.9
Electrical machinery, apparatus, energy	2.5	1.1	3.8	26.0	61%	0.8
Civil engineering	2.4	1.6	3.4	20.5	48%	0.8
Telecommunications	2.4	1.3	2.9	16.0	51%	0.8
Food chemistry	2.1	1.8	2.7	13.2	35%	0.7
Handling	2.0	1.4	3.2	19.4	51%	0.7
Machine tools	2.0	1.2	2.6	14.2	52%	0.7
Audio-visual technology	1.9	1.3	3.2	18.5	41%	0.6
Furniture, games	1.9	1.9	5.5	49.7	55%	0.6
Thermal processes and apparatus	1.8	1.5	3.9	30.0	44%	0.6
Basic communication processes	1.7	1.4	2.3	9.9	42%	0.6
Other consumer goods	1.7	1.5	2.4	11.1	48%	0.6
Materials, metallurgy	1.7	1.7	6.4	76.6	47%	0.6
Surface technology, coating	1.6	1.3	6.0	79.3	52%	0.6
Macromolecular chemistry, polymers	1.4	1.7	4.6	39.0	44%	0.5
Semiconductors	1.4	1.4	3.7	26.2	48%	0.5
Micro-structural and nano-technology	1.1	1.7	3.3	24.4	39%	0.4
Optics	1.0	1.4	3.0	19.1	47%	0.4
Textile and paper machines	0.7	1.7	3.7	25.5	43%	0.2

Note: *the relative investment is computed dividing the average investment for a specific technology by the overall average*

The number of companies developing a specific technology is quite high in the sample; with 35% and 39% of companies, Food chemistry and Micro-structural and nano-technologies are the least ubiquitous technologies. In other words, for each technological field the sample of companies developing it is quite large, reflecting the fact that large R&D investors are typically performing multidisciplinary research with competencies in technical fields outside their core ones (Patel and Pavitt, 1997). Technologies with particularly high shares of patenting companies are 'Measurement', 'Computer Technologies' and 'Electrical machinery, apparatus, energy' (at least 60%).

4.2 Determinants of technology specific R&D investment

4.2.1 Main results

The results of our estimations are reported in table 3. We present in the first column the results obtained measuring a firm's technological specialization as the share of patents in a given technology, in the other two columns we report the results obtained using RSCA computed at the sample and industry level.

Technology specific R&D investments are higher for companies with a higher share of patents in the field. In other words, developing new solutions in technical fields within the distinctive core of the company's technologies requires higher R&D investments, suggesting that keeping the edge of technological development may require additional efforts. At the same time, the (natural logarithm of) number of patents filed enters in the equation with a negative sign. Companies with higher patenting activities tend to have lower costs associated to technological development, this suggest the presence of economies of scale in knowledge production. It is worth noticing that the suggested relationship is not linear, but implies decreasing returns to scale.[12]

In the bottom part of the table we report the standard deviations of the industry and company random effects, which are in general quite high. In particular, the standard deviations of the industry specific random slopes are about half the coefficients estimated for the fixed part of the model. In other words, we find a rather heterogeneous relationship between specialisation and economies of scale in the knowledge production from one side, and technology-specific R&D investments on the other. A finding in line with the arguments put forward by Breschi, Malerba and Orsenigo (2000). The high significance of the LR-test reported at the bottom of the table supports our choice of modelling heterogeneity through a multilevel approach compared to an ordinary linear regression specification. We will come back to this heterogeneity, through a visual inspection, after commenting the results for the other variables.

The technology specific variable - number of firms developing the technology - enters with a negative sign in determining the R&D costs associated with its development. As expected, with the increase of firms developing a technology the associated R&D investment per patent tend to decrease. This could be due to the fact that the more established and ubiquitous a technology is, the more it is based on 'standard' knowledge, requiring less experimentation and risky activities (part of the uncertainty underlying technological development is resolved).

[12] For each technology we are estimating a relationship of the form $y = \beta * \ln(x)$ where investments per patent decrease linearly with the logarithm of patents. The estimated negative coefficient ($\beta = -.674$) suggests that investments per patent decrease more sharply at low levels of patenting activities than at higher levels.

Table 3: Estimating R&D-technology investments, multilevel mixed-effects linear regression

	Specialisation measure		
	Share	**SRTA (sample)**	**SRTA (industry)**
Specialisation	0.123***	3.363***	3.130***
	(0.018)	*(0.349)*	*(0.236)*
Patents (ln)	-0.674***	-0.469***	-0.398**
	(0.188)	*(0.176)*	*(0.168)*
# of firms developing the technology	-0.003***	-0.002***	-0.004***
	(0.000)	*(0.000)*	*(0.000)*
# of technological fields	0.166***	0.100***	0.067***
	(0.019)	*(0.018)*	*(0.018)*
% of international patents	0.008***	0.005*	0.005*
	(0.003)	*(0.003)*	*(0.003)*
# of foreign inventor countries	0.035**	0.034**	0.033**
	(0.016)	*(0.015)*	*(0.015)*
IPRI (2010)	-0.422**	-0.381**	-0.385**
	(0.194)	*(0.182)*	*(0.184)*
Economic area fixed effects(a)	*0.098**	*0.050**	*0.058**
Intercept	6.289***	7.895***	8.881***
	(1.496)	*(1.416)*	*(1.413)*
Random-effects (standard deviations)			
Indutry: specialisation	0.068	1.325	0.867
Indutry: patents (ln)	0.262	0.243	0.155
Industry: intercept	1.205	1.286	1.016
Company: intercept	2.281	2.136	2.145
Observations	21,133	21,133	21,122
Number of industries (companies)	15 (1,234)	15 (1,234)	15 (1,234)
Chi-2	275	226	345
LR-test	4987	5114	4099
Log Likelihood	-61511	-60548	-61306

Note: **** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (a) Reported are the p-values for the F-test of jointly significance of fixed effect; results show that overall they are not statistically significant. Random effect parameters: reported are the standard deviations of the estimated random coefficient.*

In the same direction seems to point the technological *breadth* of a company's patent portfolio which is expressed by the number of technological fields in which a company is patenting. A more extended technological base requires higher research and development costs, which may be due to a higher difficulty in dealing with the complexity of a differentiated knowledge base (Grant, 1996). Also the internationalisation of the firm's knowledge entails higher R&D investment. Indeed, higher R&D investments per patent are associated both to a higher international *depth* of the R&D activities – measured as the share of patents developed by teams with a least one inventor located in a country different from the country of the headquarters – and to a higher international *breadth* – measured as the number of countries where a company has inventors.

Are the estimated relationships economically relevant? To answer this question, we compute the implied elasticities for the right hand side variables discussed so far.[13] All the estimated elasticities are significant and sizable. Notably high are the values attached to the technological *breadth* of a company's patent portfolio and the number of firms developing a specific technology; 0.97% and -0.63%, respectively. In particular, the elasticity of technology-specific R&D investment with respect to technological *breadth* is almost unitary, which can be read as: *ceteris paribus* R&D per patent would double if a firm double its technological *breadth*. A bit lower, but still economically relevant the implied elasticities for the other regressors: 0.19% for specialisation (share), 0.13% for international *breadth* and 0.12% for international *depth*.

Interestingly, once controlling for other factors, the (headquarter) location of the company does seem to have significant effect in explaining differences across companies (de Rassenfosse and van Pottelsberghe de la Potterie, 2009). In particular, firms located in countries with a stronger legal and political protection of property rights (both physical and intellectual) show lower R&D investment per patent as indicated by the negative sigh attached to the IPRI variable (Strokova and de Soto, 2010).[14] In other words, property protection mechanisms may lead firms to a higher recourse of formal protection, which could be linked to an increased propensity by firms to patent their innovations. Finally, our results are robust to the use of SRTAs as a measure of firm specialisation. Indeed, both measuring SRTAs with respect to the overall sample or to the firms operating in the same industry do not significantly affect our results.

Coming back to the heterogeneity in the relationship between specialisation and economies of scale in the knowledge production and the technology-specific R&D investments, we provide their graphical visualisation in figure 1. In particular, in the figure we report the sum of the coefficient attached to the specialisation variable (using shares from the first column of table 3) and the best linear unbiased predictions of the random coefficient at industry level (reported in in dark blue); we do the same for the (log of) number of patents and report them in light blue.

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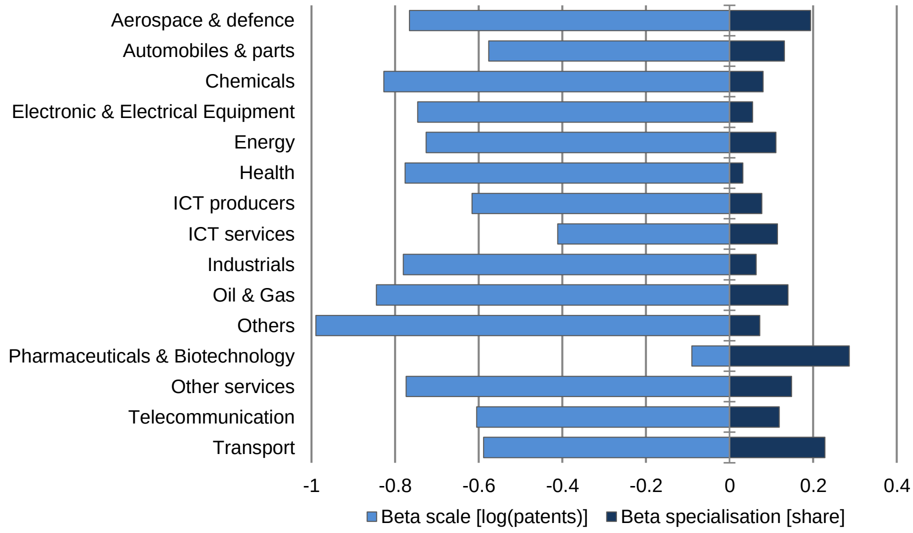
[13] The elasticity gives the percentage change of the dependent variable associated with a one percent change of an independent variable: $\eta_x = (dy/dx) * (\bar{x}/\bar{y})$, where dy/dx is the regression coefficient and $\bar{x}$ and $\bar{y}$ are the average values of the independent and dependent variable respectively.

[14] In this paper, we decided to use the international property right index instead of the international patent protection index by Park (2008), because the latter as not been updated to cover years close to our period of analysis.

Figure 1 – Specialisation and scale effects across industries



Note: *industry specific effects are obtained by summing the coefficients from the first column of table 3 with the best linear unbiased predictions of the random effects at industry level.*

The cost of specialising seems particularly relevant for firms operating in the *Pharmaceuticals and Biotechnology, Transport* and *Aerospace and Defence* industries. On the other side of the spectrum we find firms operating in the *Health* (medical machines), *Electronic & Electrical Equipment* and *Industrials*. Looking at the economies of scale in knowledge production, these seem to be strong in the *Oil & Gas* and *Chemicals*, while particularly low in the *Pharmaceuticals and Biotechnology* industry; in part at least due to the high costs associated to testing and performing clinical trials to get drugs approvals. Combining the two dimensions it is possible to grasp industry specificities which are relevant for designing policies to incentivize R&D investments and understand their possible differentiated impacts across industry. For example, in the *Pharmaceuticals & Biotechnology* industry firms face the highest specialisation costs coupled with very small economies of scale in R&D investments, here an optimal policy design would be different from that suitable for *Aerospace and Defence* (high specialisation costs, but high scale effects) or *Chemicals* (low specialisation costs and high scale effects).

4.2.2 Robustness check

Finally, as a robustness check, we report in table 4 the results of the same regressions run on a subsample of observations obtained by excluding the highest and lowest 1% investment figures. In other words, we check whether results are robust from the exclusions of those observations deviating the most from the overall sample R&D technology-specific R&D investments.

Table 4: Robustness check, trimming the highest and lowest 1% investment figures

	Specialisation measure		
	Share	**SRTA (sample)**	**SRTA (industry)**
Specialisation	0.094***	2.693***	2.471***
	(0.011)	*(0.205)*	*(0.145)*
Patents (ln)	-0.460***	-0.291**	-0.245**
	(0.129)	*(0.120)*	*(0.113)*
# of firms developing the technology	-0.001***	-0.000	-0.001***
	(0.000)	*(0.000)*	*(0.000)*
# of technological fields	0.129***	0.074***	0.046***
	(0.014)	*(0.013)*	*(0.013)*
% of international patents	0.008***	0.005***	0.006***
	(0.002)	*(0.002)*	*(0.002)*
# of foreign inventor countries	0.027**	0.026***	0.026**
	(0.011)	*(0.010)*	*(0.010)*
IPRI_2010	-0.258*	-0.235*	-0.250*
	(0.137)	*(0.126)*	*(0.128)*
Economic area fixed effects(a)	*0.051**	*0.012***	*0.019***
Intercept	3.499***	4.925***	5.693***
	(1.051)	*(0.973)*	*(0.975)*
Random-effects (standard deviations)			
Indutry: specialisation	0.040	0.843	0.616
Indutry: patents (ln)	0.099	0.169	0.094
Industry: intercept	0.415	0.721	0.601
Company: intercept	1.630	1.484	1.493
Observations	20,704	20,704	20,693
Number of groups	15 (1,234)	15 (1,234)	15 (1,234)
Chi-2	296	294	401
LR-test	3914	4176	3198
log Lik	-52634	-50988	-51815

Note: **** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. [(a)] Reported are the p-values for the F-test of jointly significance of fixed effect; results show that overall they are not statistically significant. Random effect parameters: reported are the standard deviations of the estimated random coefficient. The observations with the highest and lowest 1% values of the dependent variable are not included in the estimation sample.*

In general the results obtained for the reduced sample are similar to those discussed above. Our findings do not seem driven by the presence of observations largely deviating from the overall technology-specific R&D investments; in other words the high kurtosis presented in table 2 does not significantly affect our estimation results.

5. Conclusions

In this work we have presented a methodology to estimate the distribution of technology-specific R&D investments at the firm level and then used these values to test some arguments central in the innovation literature. To this end we made use of R&D and patent data from the top R&D investors worldwide.

Our results show that R&D investment per patent varies greatly both across technologies and across firms developing a given technology; and this despite using initial conditions implying homogeneity in our optimization algorithm. Higher investments per patent are observed in the development of new pharmaceuticals solutions, followed by those related to the biotechnology, organic fine chemistry and analysis of biological materials fields. On the other end of the spectrum, we find optics and textile and paper machines related technologies.

Firms' technological and international knowledge strategies matter in determining R&D investment per patent. The R&D investments required to deploy a new technological solution increase with the company's specialization in the specific technological field and with the *breadth* of its technological base. However, we observe (decreasing) economies of scale in knowledge production at the firm level and also lower R&D investment per patent for those technologies developed by a higher number of firms. At the same time, companies with more internationally oriented knowledge strategies - both at the intensive (share) and extensive (number of countries) margins – show higher technology-specific R&D investment.

Altogether, these findings suggest that the high and persistent heterogeneity in R&D intensity of firms operating in the same sector (Coad, 2017) can be at least in part traced back to differences in the overall knowledge production strategies, often neglected in the literature. Moreover, the heterogeneity observed at the firm level co-exists with significant differences across sectors. We find important firms' idiosyncrasies, but this does not imply that sector specificities do not matter anymore. On the contrary, our results confirm the presence of sectoral patterns of innovation activities (Pavitt, 1984; Breschi *et al.*, 2000; Moncada-Paternò-Castello, 2017). In this contribution, these sectoral patterns has been shown to be an important factor in determining R&D per patent investments, economies of scale in knowledge production, and the cost of (further) specialization.

All-in-all, our approach by focusing on the R&D investments per patent, provides insights that complement those deriving from analysing firms' returns or economic value (e.g. turnover and/or financial performances). This kind of evidence seems relevant for developing and implementing well designed R&I policies. Indeed, having better information on the 'cost side' is crucial to guide theory based policies aiming at fostering R&D investments in the economy rather than just giving (extra) prizes to the economic returns from patents (e.g. patent boxes). At the same time, we hope these results may also be interesting for technology and innovation managers in the definition of innovation strategies and allocation of resources within the company.

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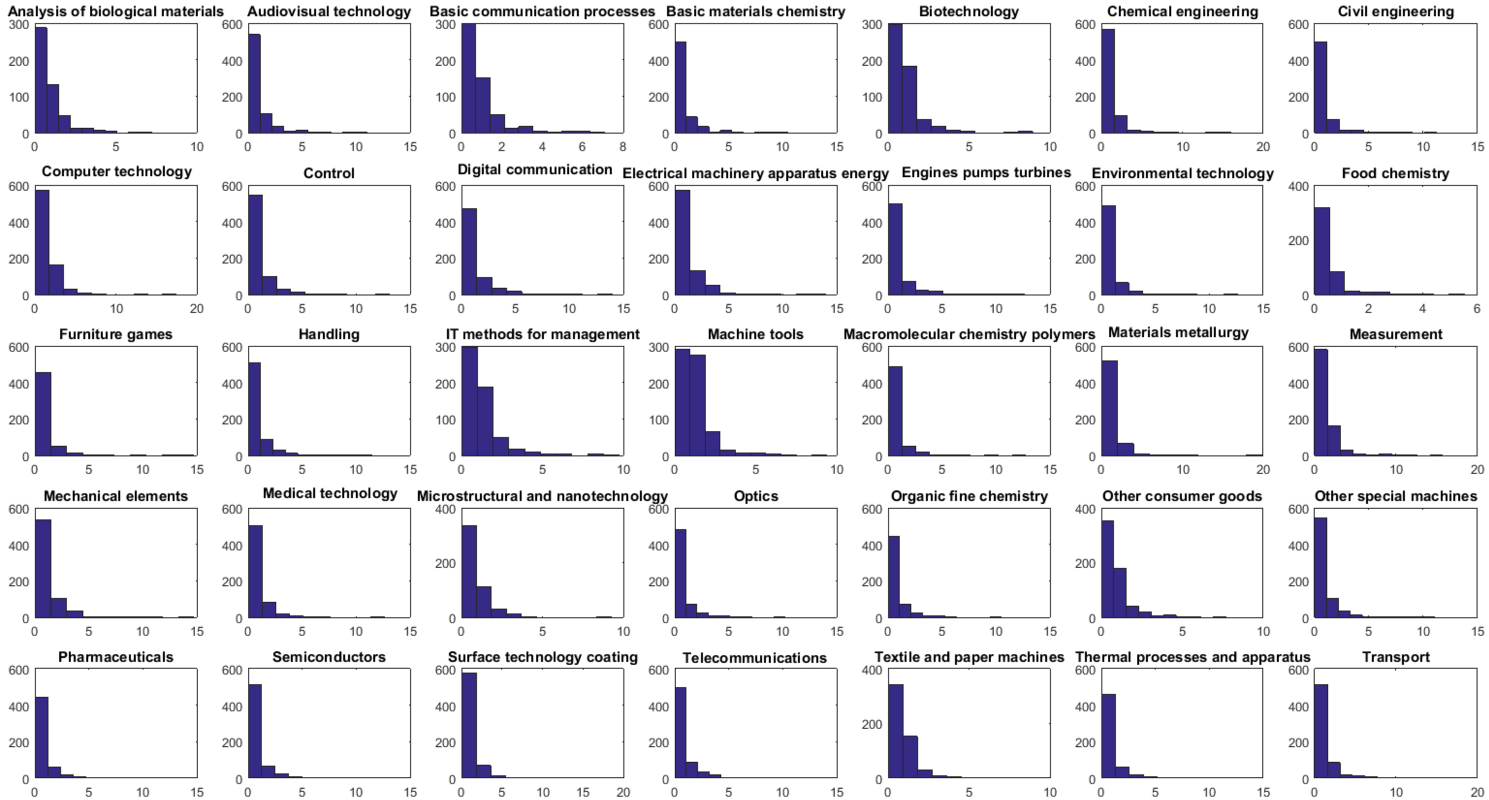
APPENDIX

Table A.1: Cost per patent and technology from the weighted average of the whole sample.

Technological fields	*Cost per patent (€ m.)*	*CV across sectors*
Pharmaceuticals	15.4	0.4
Biotechnology	9.8	0.6
Organic fine chemistry	8.3	0.6
Analysis of biological materials	7.1	0.6
IT methods for management	6.5	0.7
Transport	5.1	1.1
Food chemistry	5.1	0.9
Environmental technology	3.8	1.1
Medical technology	3.6	1.2
Engines, pumps, turbines	3.6	1.2
Mechanical elements	3.5	1.2
Computer technology	3.4	1.4
Digital communication	3.4	1.4
Other special machines	3.3	1.4
Basic materials chemistry	3.1	1.4
Control	2.9	1.7
Chemical engineering	2.8	1.6
Civil engineering	2.7	1.7
Measurement	2.7	1.5
Telecommunications	2.6	1.6
Furniture, games	2.5	1.8
Other consumer goods	2.5	1.8
Basic communication processes	2.4	1.8
Machine tools	2.4	2.4
Handling	2.3	1.9
Thermal processes and apparatus	2.3	1.9
Micro-structural and nano-technology	2.2	2.0
Electrical machinery, apparatus, energy	2.2	2.1
Macromolecular chemistry, polymers	2.2	2.1
Materials, metallurgy	2.1	2.3
Surface technology, coating	2.1	2.7
Audio-visual technology	2.0	2.3
Semiconductors	1.7	2.8
Optics	1.4	3.4
Textile and paper machines	1.3	4.6

Figure A.1: Distributions of lambdas across technological fields



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