CHAPTER 15

FROM LAB TO MARKET: EVIDENCE FROM PRODUCT DATA

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Summary

Evaluating the extent to which scientific research findings reach the market has proven to be a challenging task for scholars and policy analysts alike. Attempts have been confined to case studies of successfully commercialised research and large-scale studies of scientific publications cited in patents (as proxies for successful innovations). However, many patents are never commercialised. Besides, consumers do not buy patents, but products that embed these patents. This chapter provides proof of concept of a method that enables tracking of ideas as they progress from the lab to the market, focusing on scientific findings from Europe. The method exploits novel data on patent-protected products and links these patents to scientific articles. It then derives several stylised facts about, among others, the gestation lags of science. On average, today's investments in science will reach the market in about 20-25 years, with surprisingly little difference across scientific fields. The method appears to be a promising one to perform research evaluations of various kinds.

1. Introduction

Europe, which hosts strong higher education institutions and scientists, has a well-performing science system overall (European Commission, 2020; Schiermeier, 2019; OECD, 2017). However, the value of Europe's science base only materialises once science reaches the market, a sine-qua-non condition for generating welfare improvements and economic benefits. Turning science into innovation is a particularly challenging task, and policymakers (and, to a certain extent, administrators at higher education institutions and public research organisations) have been struggling to provide the environment that maximises the appropriation of science.

Leaving aside the difficulty of organising private (and public) markets to achieve this aim, policy analysts lack data, metrics and methods to guide them. It is notably complex to assess the impact of public funding on the production of science and, *a fortiori*, on innovation. The outcomes ('innovations') are hard to measure, and the lags between science and innovation are long and heterogeneous. Furthermore, establishing the 'but for' baseline (so-called counterfactual outcome) is notoriously difficult – concretely, establishing the innovation output we would have had without a specific policy intervention. As a result, scholarly research has focused on documenting case studies (Bastianin et al., 2021) or evaluating specific funding programs (Li and Agha, 2015; Azoulay et al., 2019).

One key piece of information that scholars and analysts have been missing so far at large scale concerns how science translates into actual products. Getting such data is critical to improving our understanding of the innovation ecosystem and, ultimately, to devising the appropriate policy tools and incentive schemes. Some recent research has analysed the extent to which scientific publications by universities reach industry by systematically tracking publications that are cited in patent documents

(Jefferson et al., 2018). However, the mere fact that a patent cites a scientific publication does not offer evidence of real-world impact. Indeed, not all patents are commercialised, and a large majority of patents are 'worthless' (Lemley and Shapiro, 2005; Moore, 2005). Besides, consumers do not buy patents – they buy products that embed these patents.

The present chapter attempts to trace ideas as they progress from the lab to the market by identifying the science behind a set of high-tech goods. It observes the science on which more than 6 000 high-tech goods build by exploiting a novel approach that has never been deployed at scale. The approach involves searching the web for patent marks, indicating which patents protect a firm's products. Therefore the analysis also serves as a feasibility study that opens the door to more fine-grained analyses of the determinants of science's market reach.

The chapter uses the data to derive several stylised facts about the market reach of scientific findings from the European continent (EU, UK and Switzerland). The most notable finding is that the gestation lags from the lab to the consumer are long. On average, today's investments in science will reach the market in about 20-25 years, with surprisingly little difference in gestation lags across scientific fields. These gestation lags typically exceed the policy timeframe and, therefore, pose a challenge to policy design and evaluation.

The rest of the chapter is organised as follows. Section 2 presents the data for the analysis. Section 3 derives some stylised facts from the data. Section 4 concludes by discussing the policy implications of the findings.

2. Data

The data for the present analysis relies on two primary sources of information: one that links products to patents and another that links patents to scientific papers. Data on product-patent links come from a novel research project, called IPRoduct – a contraction of the terms 'intellectual property right' (IPR) and 'product'[1]. IPRoduct scouts the web in search of associations between patents and products by exploiting information contained in virtual patent marking (VPM) webpages. VPM is the online provision of constructive notice to the public that an article is patented. It is the modern equivalent of physical marking, whereby patent numbers were physically printed on products. The marking statute is an old provision in US patent law, codified under Section 287(a) of Title 35 of the US Code. In 2011, the Leahy-Smith America Invents Act (AIA) added a new method of marking to the statute, allowing patentees to affix the word 'patent' or 'pat.' on the article along with a URL of a webpage that associates the patented article with the patent number(s). de Rassenfosse (2018) and de Rassenfosse and Higham (2020) provide detailed explanations of innovative firms' incentives to adopt patent marking. More information on the project is available at www.iproduct.io.

There is no VPM provision in the patent laws of European countries. VPM documents relate to US legislation and hence cover products sold in the USA. However, they offer a rich source of information for studying the reach of European science into the market for two reasons. First, the IPRoduct database includes data on European firms selling in the USA, as Figure 15-1 exemplifies with the VPM webpage of Philips, the Dutch multinational conglomerate company. Innovative European firms that sell patent-protected products in the USA have the same incentives as US firms to virtually mark their products. Second, scientific knowledge is well known to spill across international borders (e.g. Lee, 2006; Hassan and Haddawy, 2013; Tang and Hu, 2013). US firms exploit science produced not only in the USA but also in Europe. Hence, the IPRoduct database allows us to study the reach of European science. Having noted this aspect of the data, the reader should bear in mind that focusing on products sold in the USA filters out products sold only in Europe and science that non-EU firms never picked up.

Data on patent-paper links come from Marx and Fuegi (2020) and Lens.org. Both databases source the raw data by parsing the full text of patent documents in search of citations to scientific papers. A link between patent A and paper B arises when patent A cites scientific paper B (either on the front page or the body of the text). A number of recent research studies have used such data to assess the reliance on science by patent assignees and inventors (e.g. Ahmadpoor and Jones, 2017; Arora, Belenzon and Sheer, 2021; Fleming et al., 2019).

The majority of patent-protected products in the IPRoduct dataset do not rely on science (or, more precisely, have patents that do not make a direct reference to scientific papers). We find that about 37% of products in IPRoduct rely on science, totalling 6443 products. These products are covered by 8 702 unique US patents (with some protecting more than one product). Five patents protect these products on average. However, the distribution of the number of patents protecting products is highly skewed, with a median of 2 patents and a maximum of 807 patents (and an interquartile range of 3 patents). Patents in the sample collectively cite 42473 unique scientific papers (with some papers being cited by more than one patent).

1 The project is conducted at the Ecole Polytechnique Fédérale de Lausanne, Switzerland. It was started as a pilot funded by the US National Science Foundation (NSF).

FIGURE 15-1: **Philips' patent marking webpage**

PHILIPS

Consumer products Professional healthcare **About us**

Who we are News Innovation ESG Investors Careers Suppliers

About us > Innovation > About IP&S > Contact and support > Patent marking

Patent marking

In accordance with Section 287(a) of Title 35 of the United States Code, Koninklijke Philips N.V. and its affiliates hereby give notice to the public that the following products are covered by the patents identified below. The products may also be covered by other U.S. patents or pending applications.

Product Name	US Patent(s)
AngioSculpt Scoring Balloon Catheter	7686824
ComboMap System	6,265,792 6,585,660
ComboWire Wire	8231537
CORE Console	6,200,268 6,381,350 7,134,994 7,215,802 7,359,554 8,029,447 8,289,284 8,449,465 8,531,428 8,556,820 8,562,537 8,636,659 9,026,384 9,314,226 9,339,348 9,364,153 9,392,979 9,469,438 9,775,524 9,974,443

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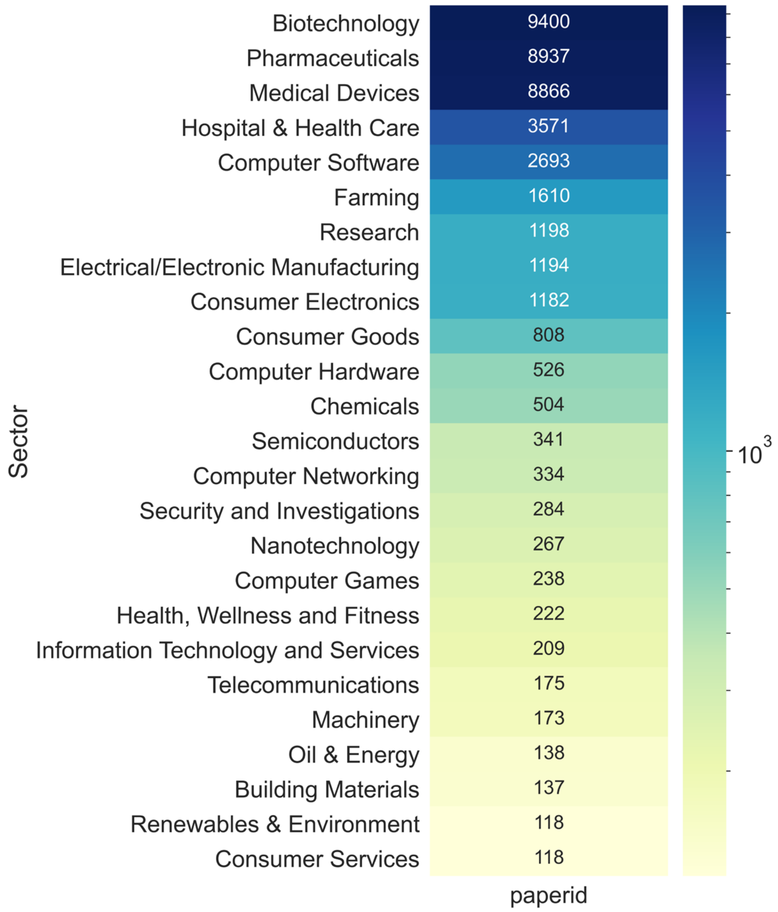
Notes: Taken from <https://www.philips.com/a-w/about/innovation/ips/contact-and-support/patent-marking.html>, last accessed 13 September 2021.
Stat. link: https://ec.europa.eu/assets/rtd/srip/2022/figure-15-1.xlsx

Figure 15-2 presents the count of scientific papers by the sector of activity associated with the high-tech goods. The vast majority of papers were published between 1980 and 2010 (see Figure 15-4). There is a predominance of publications covering health-related products, but the sample covers a wide range of sectors, including farming, consumer electronics and building materials. The following figure also provides a breakdown by field of science. It shows that biotechnology products, computer software and farming rely primarily on publications in natural sciences. In contrast, pharmaceuticals and medical devices rely primarily on publications in medical and health sciences. Publications in engineering and technology are most prevalent in consumer electronics.

Having assembled the data, the following section turns to analysing them.

FIGURE 15-2: Distribution of scientific publications by sector of activity



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Notes: Count of unique scientific publications cited by patents protecting the high-tech goods in the sample by sector of activity. High-tech goods are classified according to the LinkedIn sector of activity to which the commercialising company belongs. Sectors with more than 100 publications are reported.

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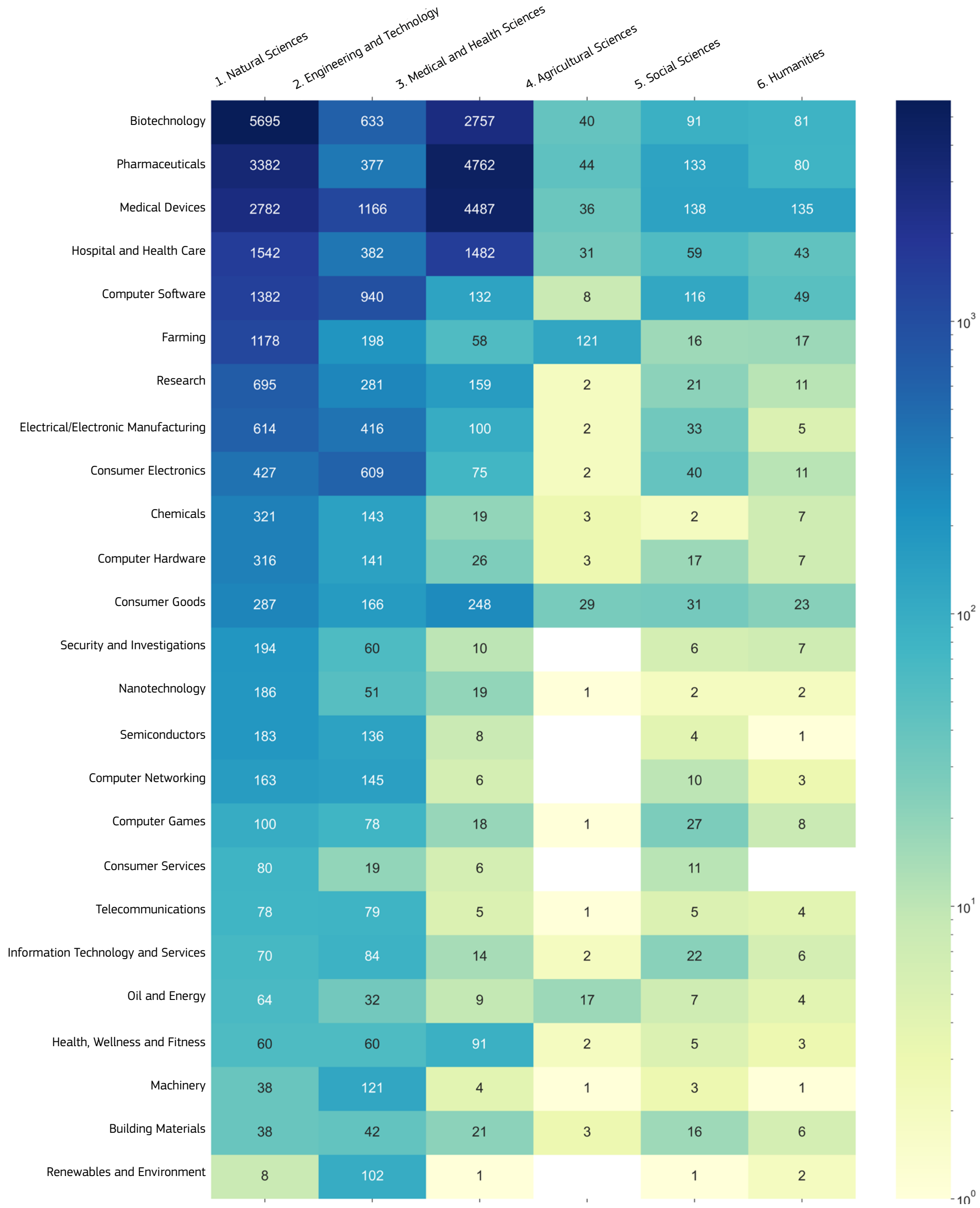
FIGURE 15-3: Distribution of scientific publications by sector of activity and field of science



Notes: Count of unique scientific publications cited by patents protecting the high-tech goods in the sample by sector of activity and field of science. High-tech goods are classified according to the LinkedIn sector of activity to which the commercialising company belongs. The allocation into fields relies on OECD's field of science and technology classification (OECD, 2007).
Stat. link: https://ec.europa.eu/assets/rtd/srip/2022/figure-15-3.xlsx

3. Stylised Facts

Science and technology gestation lags

The data inform us about the time it takes for science and technology to reach consumers. We call these time lags the 'gestation lags,' although we note that the literature sometimes uses the term 'application lags' (e.g. Kafouros and Wang, 2008). For convenience, we refer to 'science' when discussing scientific papers and 'technology' when referring to patent documents.

Figure 15-4 depicts the distribution of the publication years of scientific papers behind today's products and the distribution of the filing years of patents protecting these products. For the most part, science that led to today's products was published during the 1990s, with the median being in the mid-1990s. In other words, it takes about 25 years for scientific findings to reach the market. Notice that a significant number of scientific papers were published in the 1980s and earlier, providing evidence that the science base has a long-lasting effect.

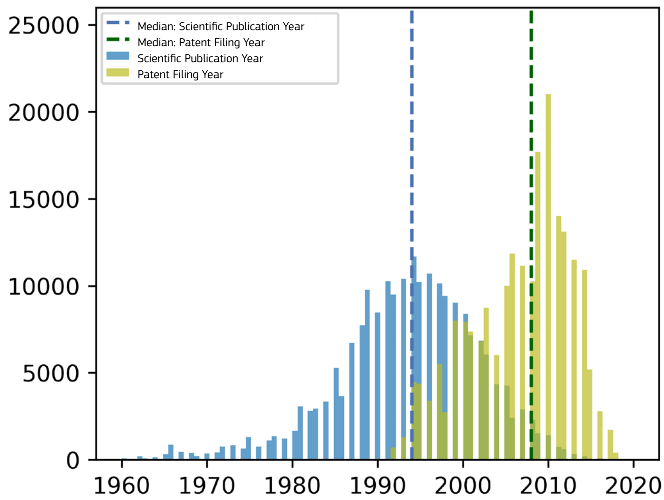
Today's products embed technology developed more than 10 years ago, based on patent filing dates. Previous research has established that the lags between R&D investments and patent filing are very short, about 1 year on average (de Rassenfosse and Jaffe, 2018), implying that today's products exploit R&D activities performed in the mid-to-late 2000s. Note, however, that we do not observe when these products appeared on the market. All we know is that these products are still available today. Should these products have been released on average 3 years ago (which is a reasonable assumption), it would take less than 10 years for R&D investments to start generating economic returns.

Despite the uncertainty about product release dates, the R&D gestation lags reported herein are relatively long compared to previous estimates. Examining the lag between R&D investments and their impact on the profits of US firms, Ravenscraft and Scherer (1982) estimated that it is about 4 years. In a similar analysis, Lev and Sougiannis (1996) found that the benefits of R&D are usually maximised in 2 or 3 years. Esposti and Pierani (2003) calibrated a model of knowledge-capital formation and came up with a gestation lag of 6 years for public R&D investment in Italian agriculture. The contrast with the literature on productivity growth is most striking, which generally assumes that R&D investment becomes productive as soon as, or soon after, it is put in place. For instance, Corrado, Hulten and Sichel (2009) consider that R&D investments instantaneously translate into productivity growth, whereas Li and Hall (2020) assume a 2-year lag. Our data challenge this assumption[2].

An apparent difference between the distributions of papers and patents is the fatter tail for scientific papers, suggesting that old science contributes to today's products, but old technology does not.

2 One potential explanation of the difference in R&D gestation lags is that we focus exclusively on commercialised products whereas models that infer gestation lags from statistical models also include process innovations, which are implemented internally by the firm (presumably at a fast rate). Another, possibly concurrent, reason is that we observe the correspondence between patents and products with high precision whereas models that infer lags from statistical models are necessarily imprecise.

FIGURE 15-4: Distribution of the publication years of science and technology contained in today's products



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Notes: An observation corresponds to a product-patent-paper triad.
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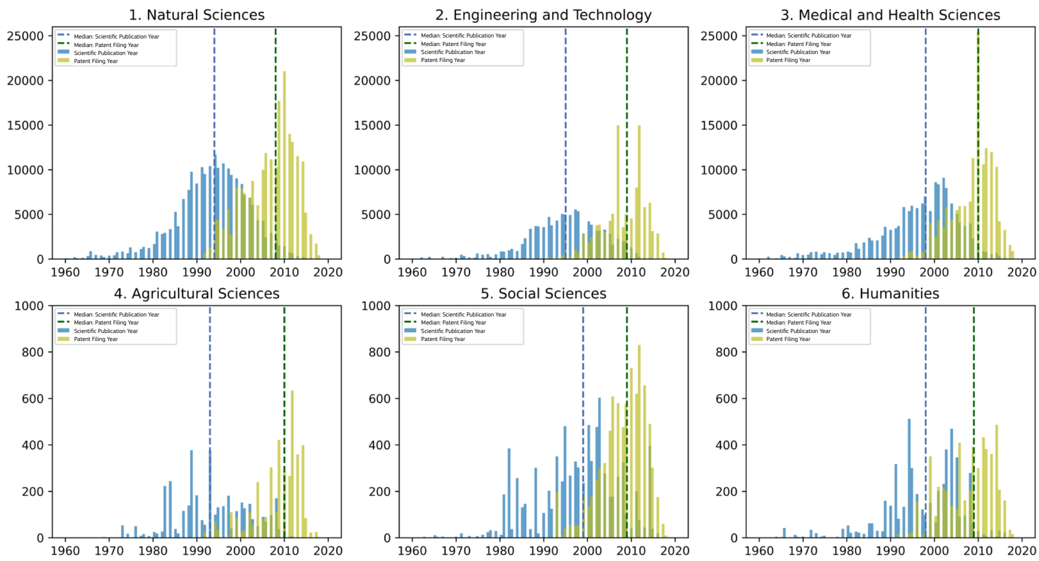
There may be some truth to this claim, but the observed phenomenon is partly an artifact of the data. Since patent rights expire a maximum of 20 years after the filing date, high-tech goods inevitably lose patent protection even if these goods are still on the market. VPM web-pages cover active patent rights, which potentially truncate the left tail of the distribution.

Figure 15-5 provides a breakdown of the gestation lags by main research field. The technology distributions look surprisingly similar across fields, with the median filing year being systematically just below 2010. The difference across fields is more pronounced for science than for technology, with gestation lags being longest for agricultural sciences and natural sciences (median in the mid-1990s) and shortest for social sciences and humanities (SSH) (median in the late 1990s). However, there is overall little heterogeneity across fields.

The literature often points to the long gestation lags for products relying on medical and health sciences (e.g. Dranove and Meltzer, 1994; Lexchin, 2021), with some drugs and medical devices having to go through lengthy regulatory approvals. However, when considering a broad set of products in this area, and not just approved drugs, the data suggest that the lags from the lab to the market are not significantly different from those in other fields on average.

FIGURE 15-5: Distribution of the publication years of science and technology contained in today's products, by field of science



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Notes: The allocation into fields relies on OECD's field of science and technology classification (OECD, 2007). Allocation based on scientific papers. An observation corresponds to a product-patent-paper triad.

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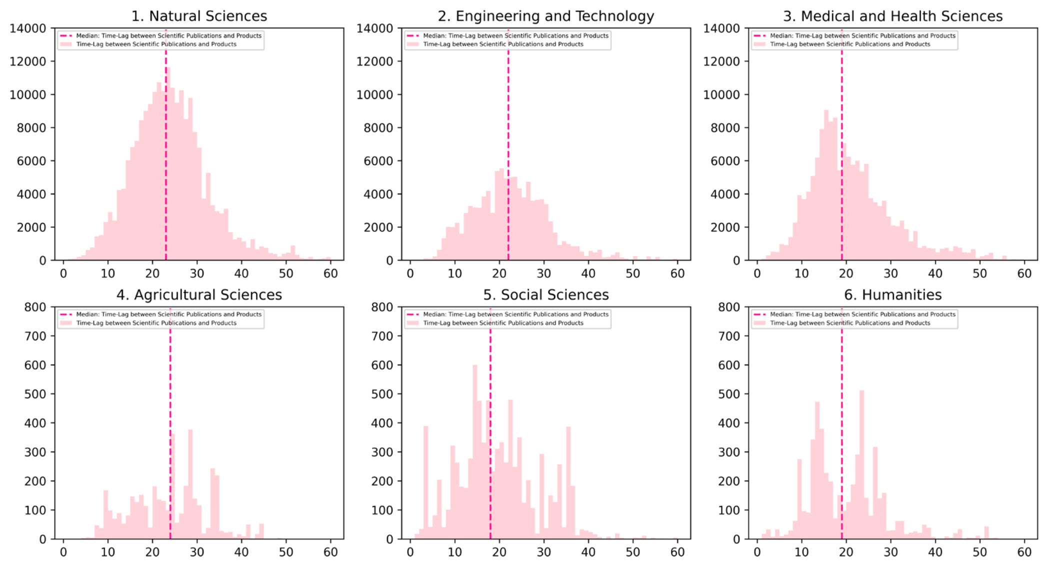
FIGURE 15-6: Distribution of science gestation lags by field



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Notes: The allocation into fields relies on OECD's field of science and technology classification (OECD, 2007). Allocation based on scientific papers. An observation corresponds to a product-patent-paper triad.

Stat. link: https://ec.europa.eu/assets/rtd/srip/2022/figure-15-6.xlsx

The figure 15-6 presents an alternative view of the lags. It depicts the number of years elapsed between the scientific publication and the product commercialisation dates (assumed to be 2017 for most products)[3]. In medical and health sciences, the average lag is about 19 years, and the mode is at about 15 years – shorter than in natural sciences and in engineering and technology.

Institutional perspective

Among scientific papers for which we were able to retrieve metadata, 56 % are published by authors from institutions in the USA (possibly involving authors from other countries but none from Europe), 23 % are published by authors from Europe (including the United Kingdom and Switzerland, and possibly involving authors from other countries but none from the USA), 3 % are published by authors from both blocs, and the remaining 18 % are published by authors from other countries[4].

3 We have chosen the year 2017 based on manual inspection of a handful of products in the sample. When a patent was filed after 2017, we set the product commercialisation date to one year after the patent filing date.

4 We could retrieve data such as DOI and authors' affiliations for 13 022 of these papers.

There is no point in interpreting the difference in the number of papers between the USA and Europe because sample composition affects these differences (remember that VPM is a provision in US patent law). However, heterogeneity within Europe is worth commenting on. We have manually cleaned the affiliation data for the top 50 European universities (belonging either to the EU-27, Switzerland or the UK) listed in the Quacquarelli Symonds QS World University Rankings[5].

Figure 15-7 provides a breakdown of the contribution of universities' scientific output to the development of high-tech goods. Universities in the UK dominate the list, with three UK universities on the podium and six universities in the top 10. Given the long gestation lags documented in the previous section, the data do not tell us much about universities' current performances. Therefore, we should not use the data presented therein to assess the performance of individual universities. However, they show the Anglo-Saxon model's dominance concerning technology transfer (e.g. Cooke, 2001; Casper and Karamanos, 2003; Searle et al., 2003). An additional explanation for the dominance of UK universities is the strong economic ties and cultural proximity with the USA.

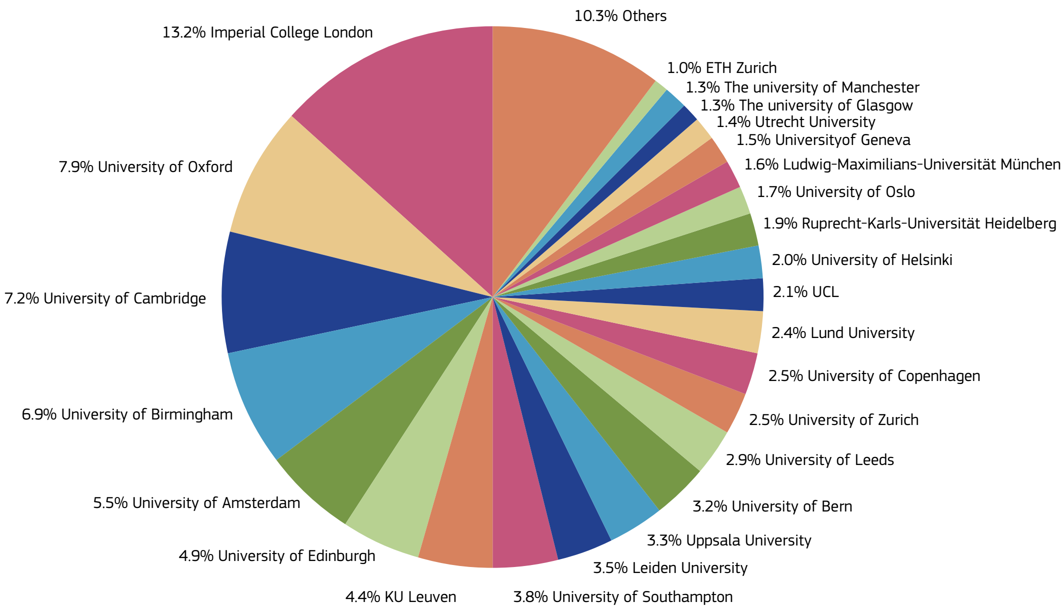
However, the data also indicate the strong performance of the 'Scandinavian model' (e.g. Benneworth et al., 2009; Bengtsson, 2017), with four universities in the top 50 for a population of about 21 million inhabitants among Norway, Sweden and Denmark.

Table 1 shows the distribution by field of cited papers for universities in the top ten. Performing an in-depth statistical analysis of the factors that drive universities' market reach is out of the scope of the present paper. Nevertheless, the table also reports the size of the universities, as proxied by the number of academic staff[6]. Two main findings emerge from the table. First, although university size seems to correlate with universities' position in the list, it is certainly not the only driver. In terms of the number of academic staff, the first-listed institution (Imperial College London) is three-fifths the size of the second-listed institution (University of Oxford), and the largest institution in the table (K.U. Leuven) is followed by one of the smallest (University of Southampton). However, we note that the last three universities listed are also the smallest, giving some credit to the hypothesis that size matters.

5 The top 50 universities are, in that order, University of Oxford (UK), ETH Zurich (CH), University of Cambridge (UK), Imperial College London (UK), UCL (UK), EPFL (CH), The University of Edinburgh (UK), The University of Manchester (UK), King's College London (UK), LSE (UK), Technical University of Munich (DE), Université PSL (FR), Delft University of Technology (NL), University of Bristol (UK), University of Amsterdam (NL), Ecole Polytechnique (FR), The University of Warwick (UK), Ludwig-Maximilians-Universität München (DE), Ruprecht-Karls-Universität Heidelberg (DE), University of Zurich (CH), Lomonosov Moscow State University (RU), University of Copenhagen (DK), University of Glasgow (UK), Sorbonne University (FR), KU Leuven (BE), Durham University (UK), University of Birmingham (UK), University of Southampton (UK), University of Leeds (UK), The University of Sheffield (UK), University of St Andrews (UK), Lund University (SE), KTH Royal Institute of Technology (SE), University of Nottingham (UK), Trinity College Dublin, The University of Dublin (IE), Technical University of Denmark (DK), University of Helsinki (FI), University of Geneva (CH), University of Oslo (NO), University of Bern (CH), Queen Mary University of London (UK), Wageningen University (NL), Humboldt Universität zu Berlin (DE), Eindhoven University of Technology (NL), Utrecht University (NL), Uppsala University (SE), Aalto University (FI), Leiden University (NL), University of Groningen (NL), and Freie Universitaet Berlin (DE).

6 Note that the data on academic staff correspond to the year 2016. These data change slowly over time and give us an indication of the relative size of institutions. Given the long gestation lags, more recent numbers are not relevant for the purpose of the present analysis.

FIGURE 15-7: Distribution of cited papers by originating university



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Stat. link: https://ec.europa.eu/assets/rtd/srip/2022/figure-15-7.xlsx

Second, it is remarkable to observe the substantial heterogeneity across universities. Overall, medical and health sciences form the most prominent category. However, this result partly reflects a sample-composition effect, as high-tech goods in the sample include many pharmaceuticals and medical devices (see Figure 15-3). Medical and health sciences accounts for more than 80% of all cited publications by the University of Birmingham, Imperial College London, KU Leuven and the University of Amsterdam. By contrast, natural sciences account for more than 80% of the cited publications by the University of Edinburgh and the University of Oxford. Other universities have a more balanced profile, including the University of Southampton and the University of Leiden, with close to 20% of publications in engineering and technology. Of course, this table tells us nothing about how 'relevant' a given field is in a given university. For instance, consider that university U has more than 20% of publications cited by patents protecting products in field F. However, these publications account for a mere 5% of U's total number of scientific publications. In that case, field F is very relevant in comparison to the other fields.

Figuure 15-8: Distribution of cited papers by field

University	Academic staff (FTE)	Field of publication		
		Natural sciences	Engineering & technology	Medical & health sciences
Imperial College	3 900	7%	1%	92%
U. of Oxford	6 390	82%	1%	16%
U. of Cambridge	5 590	18%	3%	78%
U. of Birmingham	3 040	4%	0%	95%
U. of Amsterdam	2 779	9%	4%	86%
U. of Edinburgh	4 215	92%	1%	3%
K.U. Leuven	7 094	6%	3%	90%
U. of Southampton	2 730	35%	17%	48%
Leiden U.	2 303	17%	19%	64%
Uppsala U.	2 970	36%	5%	59%

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Notes: Data on academic staff sourced from the European Tertiary Education Register (ETER) for 2016 (most recent year available). Only the three largest fields reported (agricultural sciences, social sciences, and humanities not reported).

Stat. link: https://ec.europa.eu/assets/rtd/srip/2022/figure-15-8.xlsx

4. Policy discussion

This chapter provides proof of concept of a method that enables tracking of ideas as they progress from the lab to the consumer. Scholars and policy analysts, who have lacked such data in the past, can use the method to study factors that facilitate technology transfer (at the university level or the level of the regional or national higher education systems, see Williams et al., 2013). Having applied the method to study the reach of European science into the market, the empirical analysis has uncovered five main findings that have policy implications.

First, the gestation lags from the lab to the consumer are long. On average, today's investments in science will reach the market in about 20-25 years. While experts are familiar with such lags in products exploiting medical and health sciences, the figure is remarkably stable across scientific fields. These long lags exceed the typical policy timeframe and, consequently, pose an immediate challenge to policy evaluation.

Second, the science base has a long-lasting effect, with some papers published in the 1980s and earlier still contributing to today's technological progress. Although this finding does not come as a surprise, it is a helpful reminder that the opposite also holds: reducing the knowledge base today has long-lasting consequences.

Third, all fields of science contribute to commercial products, including SSH. However, translation (of the sort we can observe in our data) occurs primarily in natural sciences and medical and health sciences. Scientific papers in engineering and technology represent the third-largest group. We caution against using this finding to conclude that SSH research has no real-world impact. Our method tracks science embedded in products, which is not a typical outcome for SSH research. For SSH, this research requires alternative evaluation methods that consider their social and political impacts (Reale et al., 2018; Pedersen et al., 2020).

Fourth, universities exhibit very heterogeneous profiles regarding the fields of science that are being translated. Whereas some universities are very strong in one field, others have a more balanced profile. This finding suggests that there is no dominant discipline when it comes to research impact. Note that, given the incomplete data on which the analysis builds, the list of universities should not be taken as a ranking especially not a ranking of the current performance of universities given the long gestation lags uncovered above. Although there is merit in benchmarking universities by exploiting such data in the future, a careful analysis that accounts for various statistical and data collection pitfalls is warranted.

Fifth, turning to country-level 'performances' on the European continent, the UK university system seems to contribute the most to high-tech goods, probably driven by the biotechnology revolution (see, e.g., Searle et al., 2003). Interestingly, Scandinavian countries are punching above their weight, with four universities in the top 50. It would be worth investigating the reasons behind this phenomenon in follow-on research.

More generally, this chapter has illustrated that data for Europe are patchier than for the USA. However, this does not need to be the case. To help us collect data, the inclusion of virtual marking provisions in the patent laws of European countries would be particularly helpful. To improve further the data infrastructure of EU science policy, systematically tracing linkages from scientific papers to European patents – and making the data openly available – seems a natural first step.

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