Acquisitions, inventors' turnover, and innovation: Evidence from the pharmaceutical industry

Carmine Ornaghi [a,*] , Lorenzo Cassi [b]

[a] *University of Southampton, Southampton, United Kingdom*
[b] *Université Paris 1 Panthéon-Sorbonne, CNRS, Centre d'Économie de la Sorbonne, Paris, France*

ABSTRACT

This paper examines the relationship between the post-merger decline in patenting among pharmaceutical firms, as observed in previous firm-level studies, and the following individual-level dynamics: (i) the exit of inventors from the innovation market, (ii) the departure of inventors from target firms to other research labs, and (iii) a decline in the innovative output of inventors who remain within the acquired firms. Using a large sample of target companies, we estimate that acquisitions are associated with an increase in exit rates of inventors between 7.6 and 17.5 percentage points and of their departure rates ranging from 12.2 to 18.9 percentage points. We find similar results are obtained for large and small deals and that top inventors of targets are also more likely to exit or to leave when an acquisition takes place. Our results show that, for each inventor that exits the innovation market, around 2 patents are foregone, representing more than 30 percent loss of the expected output these scientists could have produced over their careers. Inventors who relocate to a different lab also generate 2 fewer patents compared to similar control scientists, representing a 30 percent decrease in their productivity too. Finally, inventors that stay at the acquired targets also experience a decrease in output of nearly one fewer patent. These results point to a significant decline in both human capital and consumer welfare, which call for a closer scrutiny of M&As.

1. Introduction

Innovation is a key driver of firms' productivity growth, product quality improvements and economic growth more generally. One question that has gained central stage in the economic debate on innovation among academics and antitrust authorities is how changes in market structure affect firms' research incentives and capabilities. Specifically, in recent years there has been a growing concern among competition enforcers that mergers and acquisitions (M&As) involving highly innovative companies in concentrated industries

may decrease research effort and output.[1] These concerns have not been dissipated by theoretical studies, for these have shown that M&As may spur or stifle innovation depending on the assumptions made about the R&D technology, the synergies arising from the merger and changes in the appropriability of innovation.[2] Ultimately, the question of whether M&As have a positive or a negative impact on innovation is therefore an empirical one, and can be properly addressed only by considering the idiosyncrasies of each industry.

Looking at the case of the pharmaceutical industry, where innovation is a fundamental driver of medical advancements, empirical studies have consistently found a significant decline in the number of patents after a consolidation – see Ornaghi (2009a) and Haucap et al. (2019). This trend can be attributed to the fact that the post-merger restructuring often involves the pruning of research projects, and the layoffs of R&D personnel,[3] as well as to the fact that integration challenges can hinder the realization of anticipated knowledge synergies and lead to a decrease in the production of new knowledge of researchers within the consolidated firms.

From the societal point of view, the post-merger reduction in the number of patents of consolidated companies found in previous studies has very different welfare implications depending on whether it is coupled with a drastic increase in the number of scientists who stop doing productive research or is instead associated with an increase in the number of scientists moving to other pharmaceutical companies. In the former case, mergers lead to a loss of human capital, and, in turn, several inventions that could have ultimately resulted in the production of more cost-effective treatments, will not see the light of day. In the latter case, the reallocation of human capital might lead to an increase in productivity if the new company represents a better match for the scientists' skills.[4]

In this paper we follow the career of scientists of pharmaceutical firms using data from the European Patent Office (EPO) to provide novel evidence on the relationship between acquisitions and innovation at inventor level. Specifically, we examine the following three dynamics: (1) whether inventors of target companies are more likely to stop patenting (*exit rate*) and, if so, the number of patents they could have produced (lost patents); (2) whether inventors of target firms have a higher probability of moving to another company (*separation rate*)[5] and whether such move is associated with an increase or deterioration in their productivity ;[6] (3) how the productivity of inventors who remain at the target firms change after their acquisition.

We retrieve the patent history of hundreds of thousands of inventors that have worked for a pharmaceutical company between 1978 and 2015, as well as detailed information about M&As in the pharma industry between 1988 and 2015. We extensively process the information of patent applicants (i.e. pharmaceutical firms) to derive the employment history of these inventors, including details about their latest patent (*exit*) or any move to a new company (*separation*). To externally validate the quality of our newly constructed dataset, we matched a subset of our inventors to LinkedIn data. The comparison suggests that both our inventor disambiguation procedure and career tracking are fairly accurate (see Appendix A for details).

The use of inventor-level data, combined with a dynamic classification of target firms linked to parent companies, enables us to track inventors' career trajectories over time. This approach allows for a more rigorous analysis of post-merger changes in patenting dynamics compared to firm-level studies, as individuals, unlike firms, do not merge into a new entity.

Our empirical analysis compares whether the probability of observing an exit or separation differs between inventors working for firms that are object of an acquisitions and those that are not. In line with most of the existing literature, we do not investigate exit and separation rates for inventors of acquiring companies because large pharmaceutical companies, which employ a significant proportion of the inventors in our dataset, are frequently involved in the acquisition of small and medium-sized labs. Consequently, their inventors would always be classified in the "treated" group, even though most of these deals have no influence on their research activities.

Our analysis provides robust evidence that there is a substantial increase in both the exit rate and separation rate of scientists of target firms around the period of consolidations. Specifically, we find that the likelihood of exiting our dataset increases by 7 to 17 percent and the probability of moving to a new company rises by 12 to 18 percent. This finding is robust to controlling for a variety of inventors' characteristics such as their cohort (year of their first patent), inactivity (years passed since the last patent), experience (years since the first patent), productivity (total number of patents over a given period), and its quality (total number of patents and forward citations over a given period). We also include the size of firms' patent portfolio as well as firm fixed effects, which help us control for unobservable (time-invariant) characteristics such as company culture and managers' strategic approach to consolidations. Our findings hold also when we include technological class fixed effects to control for differences in the inventors' area of specialisation. In addition, the robustness of our findings is confirmed across a range of empirical checks. In particular, the inclusion of financial indicators from Orbis to control for firms' selection into treatment, as well as a matching-based estimation framework, yields results that closely mirror our baseline findings (see Section 5.3 for details).

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[1] Gilbert and Greene (2015) note that, during the 2004–2014 period, the US Antitrust Agencies mentioned innovation-related concerns in about a third of the deals they challenged. At the same time, the European Commission referred to an innovation theory of harm in different merger cases, most notably in Dow/DuPont and GSK Oncology/Novartis.

[2] See Federico et al. (2017), Denicolo' and Polo (2018) and, more recently, Moraga-González *et al.* (2022) and references therein.

[3] After Glaxo acquired Wellcome in 1996, Wellcome's main U.K. research facility in Beckenham (with 1,500 scientists and staff) was closed and GSK lost more talent than they expected (Ravenscraft and Long, 2000). Similarly, following the acquisitions of Warner Lambert and Pharmacia Corp in the early 2000s, Pfizer shut down R&D operations in Michigan and Illinois (https://www.fiercebiotech.com/pharma-mergers-cutbacks-badly-damaged-research).

[4] See Gilje et al. (2022) for a recent study on human capital reallocation following firm-specific shocks using data of the UK football premier league.

[5] In this paper, we use the terms 'separation rate' and 'departure rate' interchangeably.

[6] The analysis of the effects of mergers on productivity of inventors of target firms that continue working for the acquiring companies is the objective of a companion paper (Cassi and Ornaghi, 2024).

Importantly, our study also reveals that the dynamics described above are unexpectedly similar across inventors of different stature. Whereas we find that the most productive scientists are, in normal circumstances, less likely to exit the market of innovation, at the time of acquisition the likelihood of exit increases for all inventors. This finding is particularly interesting because it suggests that our results are not due to optimal scientists' selection, i.e., the fact that acquirers could strategically and optimally choose to retain the scientists who are more likely to make major breakthroughs, while getting rid of those working on less promising projects.[7]

Next, we proceed to quantify the number of lost patents due to the increased exit rate as well as changes in productivity for both inventors that stay and those who move to a new lab. To achieve this, we match inventors of target companies to inventors working for firms that have not involved in merger, but with similar productivity and career history up to the date of the merger. Even if inventors of target firms who are observed to stay, to leave and to exit, may not be a random sample, as merging companies try to retain their best scientists when consolidating their R&D activities, our identifying strategy is valid under the mild assumption that innovation activities are characterized by such a level of uncertainty that the observable inventors' patent history is the best predictor of their future productivity and thus very informative on any unobserved selection mechanism. In this respect, a key advantage of using inventor-level data over firm-level studies is that, for each *treated* inventor (i.e., an inventor from a target company who exits, leaves, or stays), we can select a *control* scientist from a large pool of individuals who do not work for firms targeted for acquisition. Our findings suggest that, for each inventor that exits the innovation market, around 2 patents are foregone, equivalent to more than 30 percent of the expected output these scientists could have generated throughout their careers. Inventors who relocate to a different lab also generate 2 fewer patents compared to similar control scientists, representing a 30 percent decrease in their productivity. Finally, inventors that stay with the acquired targets also experience a decrease in output of nearly one fewer patent. Interestingly, this decline is driven by inventors who do not collaborate with colleagues from the acquiring companies, whereas "collaborating" inventors experience only a marginal decrease. The high exit and separation rates, along with the decline in productivity among inventors that remain, appear to contradict the idea that consolidations are driven by the desire to acquire a pool of talent and create synergies between the research teams of the target and acquirer, as often invoked by firms to justify such deals. On the contrary, our results show that mergers are associated with a significant depletion of human capital due to the exit and departure of scientists and with a substantial loss in social welfare, to the extent that these scientists could have produced new knowledge instrumental for the development of more cost-effective treatments.

Our findings speak to two debates in competition policy that have largely evolved in parallel: the impact of mergers and acquisitions on innovation, and the effects of consolidation on worker welfare.[8] This separation is surprising because technological progress and human capital are closely linked: innovation is rarely manna from heaven, but the product of human effort and expertise. The issue is particularly salient in Europe, where calls for a more active industrial policy have intensified, often emphasising consolidation as a means of creating "European champions" (see Scott Morton, 2024). While such mergers are frequently justified on grounds of scale and efficiency, our results highlight a channel through which they may instead weaken innovative capacity: the disruption and loss of specialised human capital. This suggests that competition and industrial policy should be assessed jointly, with policy choices grounded in careful empirical analysis rather than a priori assumptions about the benefits of consolidation.

Related Literature. Our paper is related to three strands of literature. First, several empirical studies in the field of industrial organisation have investigated the relationship between M&As and innovation in different sectors, using firm-level data on R&D and patents - see Colombo and Rabbiosi (2014), Entezarkheir and Moshiri (2018) and Bennato el al. (2021), and references therein. Ornaghi (2009a) and Haucap et al. (2019) are among the most comprehensive works investigating the effects of M&As on patent output for the specific case of the pharmaceutical industry.[9] Their analysis focuses on mergers among large companies: 27 merger deals signed between 1988 and 2004 in Ornaghi (2009a) and 65 mergers between 1991 and 2007 in Haucap et al. (2019). Both studies find that mergers are associated with a decrease in innovation effort, indicated by a reduction in R&D expenditure, and a decline in innovation output, as measured by patents. Indeed, their results suggest that the reduction in patents is far greater than the cuts to R&D spending: Ornaghi (2009a) finds that patents fall by between 10 % and 20 % in the 3 years following an acquisition, in contrast to a 5 %−10 % drop in R&D expenses ;[10] Haucap et al. (2019) observe a 30 % drop in patents with R&D cuts of around 20 %. However, as R&D expenditure covers all research activities, from basic science to the clinical trial stages (see Section 2, for details), it is difficult to say whether these (aggregate) figures point to an increase in the R&D spending for each unit of knowledge output measured in terms of patents. By using inventor-level data, we can investigate whether the decrease in patenting observed at firm level is associated with a halt in inventors' activity (human capital loss) or rather a migration of inventors to other research labs (human capital reallocation).

Our findings are also related to the influential paper by Cunningham et al. (2021), which finds that acquisitions in the pharmaceutical industry often led to the discontinuation of target's innovation projects when these overlap with the acquirer's existing product

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[7] This result also corroborates the thesis that, in the pharmaceutical industry, acquiring firms can strategically target firms based on their portfolio of marketed products, pipeline projects, and IP. However, acquisitions are seldom driven by the desire to hire key individuals or a whole team of scientists (see Cunningham *et al.*, 2021, Section 5.1,4).

[8] A 2016 report produced by the White House's Council of Economic Advisers highlighted that 'antitrust laws apply to reductions in competition for employees as a result of mergers as readily as they do to reductions in product market competition'. There has been a growing effort to study the labour monopsony concerns associated with consolidations (see Marinescu and Hovenkapm, 2018).

[9] See also Grabowski and Kyle (2008) for a review of the determinants and effects of M&As in the pharmaceutical industry

[10] In a related study on the pharmaceutical company, Ornaghi (2009b) finds that the decrease in R&D expenditure is higher when there is a large overlapping between the technologies of merging companies.

portfolio, notwithstanding the following two differences, among others. First, our analysis concerns the research phase - the R in the R&D - whereas their study mainly focuses on the development of new treatments (see Section 2, for details)[11] Second, the three authors forcefully argue that 5 to 7 percent of acquisitions are solely motivated by the desire to kill the target's innovation. In this paper we highlight the detrimental effect of M&As on scientists' productivity, without taking a stand on whether the post-merger dynamics we document are the outcome of deliberate decisions to eliminate competing research projects,[12] or the unintended consequences of cultural clashes and other integration problems, which may trigger the unexpected exit and departure of key employees.

Second, our work is related to the large and growing management literature on the relationship between M&As and labour turnover (see Wang (2024) and reference therein). M&As are often used as a strategy to hire the knowledge embedded in a target company's workforce. However, the success of this strategy relies on managers' ability to forge a common corporate culture and integrate the merging parties' knowledge capabilities - see Gomez-Mejia and Palich (1997) and Cloodt, Hagedoorn and Van Kranenburg (2006), among others. An early study by Ernst and Vitt (2000) finds that mergers lead to the unexpected departure of several key inventors. This finding is consistent with more recent work by Ng and Stuart (2022) and Kim (2020), which compares turnover in tech start-ups in the US among acquihired personnel and workers hired organically through standard processes. Both studies find higher turnover rates among employees of target firms compared to employees hired through organic channels,[13] an effect that is greater for more senior, educated, and high-earning employees. In examining the impact of M&As on German companies between 1997 and 2014, Gehrke et al. (2021) also find a 7.6 % increase in worker turnover rate.[14] Similarly, Verginer et al. (2025) find that inventors in acquired biotechnology firms are 20 % more likely to leave within five years compared to a control group.

Two studies closely related to ours are Wang (2024) and Verginer and Riccaboni (2025). The former investigates human capital reallocation following mergers and acquisitions, focusing on retained, departed, and newly hired inventors across multiple industries, whereas we concentrate on target inventors in the pharmaceutical sector, for the reasons discussed above. Despite these differences, several of their findings align with our results, including a significant increase in the departure rate of target inventors (by 5.6 to 5.9 percentage points) and a decline in their patent output. The latter examines how acquisitions in the biotech industry affect inventor productivity and retention, using data from 1990 to 2010. Employing a staggered difference-in-differences approach, they report a 13.5 % increase in inventor turnover and a 35 % decrease in patent productivity following acquisitions, which are in line with our findings.

Third, this paper is related to the macro literature exploring the long-term effects of human capital reallocation on productivity following a firm-specific shock. A consistent finding of this literature is that, after mass layoff, displaced workers lose some of their firm-specific human capital and become less productive in their new job vis-a-vis how they would have been if they had not been displaced – see Jacobson et al. (1993) and Lachowska et al. (2020).[15] In the context of job losses due to M&As, a recent study by Arnold et al. (2023) investigates the effect of acquisition on productivity by looking at the change in earnings of displaced workers. They estimate a decrease in income of around 4 percent, due to job transitions to employers with poor match qualities.

The present paper differs from the existing literature in one or more of the following aspects. First, we offer a comprehensive analysis of the impact of acquisitions on inventors at target firms in pharmaceuticals, one of the most important and highly innovative industries.[16] Specifically, we simultaneously examine exit rates and separation rates, exploring how these dynamics vary across scientists of differing stature. Furthermore, we provide novel evidence on changes in the productivity of inventors who remain and those who leave the target firms, as well as estimates of the number of lost patents associated with increases in exit rates. Second, the scale of this project is substantially larger than many previous studies: we consider more than 500 deals, consummated among pharmaceutical firms between 1988 and 2015. Our newly constructed dataset includes hundreds of thousands of inventors with at least one patent classified in the pharmaceutical space. Whereas in firm-level studies the donor pool to construct the control group includes only a few hundred companies at best, the fact that we can also observe thousands of inventors that work for firms not object of an acquisitions means that we can easily match inventors of target companies (the treated group) to a control group of inventors that have identical characteristics, including their patent output, up to the year of the merger.

The remaining of the paper is organized as follows. After describing the main features of research and patenting in the pharmaceutical industry in Section 2, Section 3 explains the data set and variables used, with particular emphasis on the construction of patent statistics and inventors' mobility. Section 4 describes the empirical methodology and Section 5 presents the results. Finally, we conclude by discussing the important implications of our results for merger control enforcement.

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[11] In the ancillary results on inventors' productivity and mobility following acquisitions, Cunningham et al. (2021) document that 78 percent of target firm inventors move to other companies, a figure significantly higher than those reported in the literature. Since their data are not retrieved from international patent offices, we believe this discrepancy arises because they focus on a selected group of inventors.

[12] Comanor and Scherer (2013) argue that M&As adversely affect R&D investment and new drugs development because of the desire to eliminate projects that are, often wrongly, perceived as duplicative.

[13] Kim (2020) finds an increase of between 10% and 20% in the departure rate.

[14] Hussinger (2007) is one of the few studies that finds that key inventors in the targeted firm are more likely to remain at the same firm.

[15] Lachowska et al. (2020) find that "Loss of valuable specific worker-employer matches explains more than one-half of the wage losses."

[16] Our study was developed independently and simultaneously with Verginer et al. (2025) and Verginer and Riccaboni (2025), who also examine acquisitions in the pharmaceutical sector. While their work focuses on firms' R&D strategies from a management perspective, ours addresses the economics of acquisitions in the pharmaceutical industry and their implications for competition policy, offering a complementary and original contribution.

2. Patents, acquisition and inventors' status

In this section, we begin by describing the unique characteristics of innovation activities in the pharmaceutical industry, which provides important context for understanding how patent data are used to address our research questions. We then discuss how acquisitions affect the careers of inventors in target companies and, in turn, the classification of scientists' status in the post-acquisition period.

R&D in pharma consists of two very different stages: pre-clinical *research* and clinical *development*, henceforth referred to as the *R stage* and *D stage*. In the *R stage*, chemical and biological compounds are screened for attractive therapeutic and pharmacological properties in vitro. A molecule that exhibits the potential to treat a certain condition is then tested in vivo, typically in laboratory-bred mice, to investigate how it is absorbed, distributed, metabolised, and excreted (pharmacokinetics), its mechanism of action and potential benefits (pharmacodynamics), and side effects or adverse events (toxicity). Major pharmaceutical and biotechnology companies spend between 15 % and 30 % of total annual R&D costs on non-clinical research.[17]

A compound that successfully completes the pre-clinical tests (on average, one among 5000–10,000 screened), moves to the *D stage*. Here, scientists test the efficacy and safety of the compound on humans using clinical trials. Clinical development consists of three different phases. In Phase I, a battery of tests on toxicity and safe dosing ranges are performed on a small number of healthy volunteers. Compounds that are found to be safe then progress to Phase II testing on a larger group of individuals that are affected by a certain condition to verify the beneficial effects of the drug and to continue the safety assessment in a larger group of patients. If there is significant evidence of efficacy, then the compound moves to Phase III. Here, the drug is tested on a large sample of patients with the aim of more accurately evaluating the actual benefits and possible adverse reactions (DiMasi, et al., 1991). Failure rates during the three phases of clinical trials are very high. In 2016, only 81 new drugs were launched in the EU (and 56 in the US) while >7000 compounds were at different phases of development worldwide, a testament to the research hurdles that need to be overcome before a compound can be developed into a safe and effective drug.

The high level of competition in the pharmaceutical industry means that it is likely that a new compound discovered by one company may be discovered by a rival company soon after. Given the importance of being 'the first to file' in a patent race, companies typically submit patent applications on promising new compounds at the end of the *R stage*, before even starting clinical tests on humans. Note that pharmaceutical companies do not only apply to patent protection on new molecules, but also to aspects such as the manufacturing process, formulation, and delivery.

To summarize, although most patents awarded to pharmaceutical companies pertains to activities and compounds that do not provide an immediate benefit to patients, patents are a reliable and comprehensive measure of *R-stage* activities and are particularly useful for tracking the employment history of scientists.

Building on this foundation, we next describe how patents are used to track the career trajectories of inventors at target firms and classify their status following an acquisition. Specifically, as shown in Fig. 1, we assume that the restructuring process begins with the acquiring firm deciding whether to retain or lay off inventors. Around the same time, inventors may seek and receive external offers, which they can choose to accept or decline. Inventors who are laid off and do not secure external offers exit the innovation workforce altogether, while those who are laid off but do receive offers are likely to accept them. Inventors retained by the firm may also receive and potentially accept external offers. Inventors who remain in the workforce resume doing their research, either in their current lab (albeit under the new structure) or in a new one, and they have a probability "*p*" of producing new knowledge in the form of patents. For simplicity, the graph assumes that the probability is the same across all nodes. However, if merging firms successfully retain their most productive scientists, or if only high-quality scientists are likely to receive external offers, the likelihood of obtaining a new patent may vary across these nodes because it arises not solely from randomness but also from the quality of the inventors.

Fig. 1 illustrates that inventors of targets in our dataset are finally classified in one of the following three different groups: stayer, leaver and exit. The exit category encompasses a variety of scenarios: from inventors who are laid off and do not receive external offers (probably because of their low productivity), to inventors who remain employed by the same company but may engage in research projects that fail to result in patentable innovations. In contrast, there is only one path that leads to classifying an inventor as a stayer: the inventor must produce a new patent in the post-merger period, with the assignee name reflecting the new structure of the company (typically the name of the acquiring company or a newly established entity). Since inventors are not randomly classified in the three groups but rather, this classification results from the decisions made by both firms and the inventors, the analysis of these three "treated" groups requires the use of appropriate control groups, a procedure detailed in Section 4.

3. Data and variables

To build our analytical dataset at inventor level, we use data drawn from two distinct sources: the PatStat/EPO dataset,[18] which records comprehensive information on patent applicants (generally, firms) and scientists' patent activities, and Orbis and Zephyr databases,[19] published by Bureau van Dijk (BvD), which provide us with, respectively, financial information on pharmaceutical

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[17] See the 2021 report of the US Congressional Budget Office on "Research and Development in the Pharmaceutical Industry" and Figure 1 of "Facts and Figures 2022: The Pharmaceutical Industry and Global Health" published by the International Federation of Pharmaceutical Manufacturers & Associations (IFPMA).

[18] Version PatStat 2017, March.
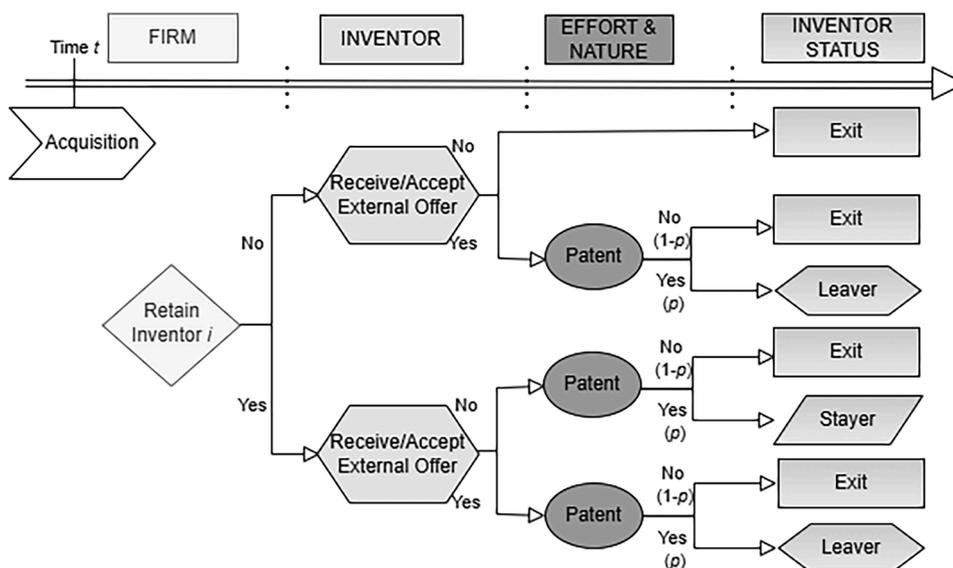
[19] Downloaded in April 2016.

Fig. 1. Inventor Status: Exit, Leave and Stayer.

companies around the globe with their group structure, and a list of M&As in the industry.

To carry on our analysis, we use the sources above to build an original dataset that can track the career of inventors across different pharmaceutical groups. To this aim, great effort has been devoted to deal with the following two challenges. The first hurdle is that PatStat, like other similar datasets, often updates the name of the firm that owns the patent when there is a change in ownership, thus implying that the acquiring firm may be erroneously listed as the applicant. Accordingly, a lot of effort has been devoted to reassigning all patents to the original applicant. The second challenge consists in using information on ownership changes, such as mergers, acquisitions, and disinvestment, to reconstruct the ownership structure of pharmaceutical groups (mother companies and subsidiaries) over time.[20]

In the next subsection we describe in detail all the steps we followed to construct our analytical dataset. But before doing that, two clarifications about patent data are in order. First, patent data enable us to track the career of scientists much like journal publications allow us to follow academics' institutional affiliations, and in turn to infer their mobility. Accordingly, we can observe whether scientists remain with the same organisation or move to a different one only in cases where they have more than one patent. One inherent limitation of patent data, as for publication records, is that we cannot track scientists' employment status after their last patent. Specifically, a scientist who is no longer named on any patents may have retired, changed career or remained in their job but produced no further patentable knowledge. We use the term exit in this paper to cover all three potential outcomes, as they all denote a scientist who is no longer observed in our data.

Second, one of the main criticisms of the use of patents to measure innovation in the pharmaceutical industry is that patent-based analysis does not identify molecules and treatments that are developed and, eventually, commercialised. This criticism is not relevant for the research questions addressed in this paper. First, as explained in Section 2, patents represent a reliable measure of new knowledge produced, though mainly at the drug discovery stage rather than the drug development stage. Second, we use patents not to construct firm-level measures of innovation, but to compute exit rates and separation rates. In this respect, pharmaceutical companies' well-known tendency to use patents to protect their know-how more extensively than firms in other industries - even though some patents may be used as strategic tools to block the entry of competitors or as 'bargaining chips' in patent litigation (Hall and Ziedonis, 2001) - means that we can construct precise measures of inventors' quality and mobility.

3.1. Patents, inventors and pharma groups

In this Section 3.1 we detail the three-step procedure we have followed to construct an analytical dataset that allows us to track scientists' career over time considering, on the one hand, the original applicant, and on the other hand, the dynamic change of firm ownership structure.

Step I: Identification of Inventors. Our empirical analysis refers to the patenting activity of all inventors with at least one European patent application in the pharmaceutical field, broadly defined.[21] However, to track the entire patenting history of all these inventors,

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[20] Arora et al. (2021) has accomplished a similar task of dynamic reassignment of patent relative to the NBER patent data.

[21] Based on Schmoch (2008)'s classification of 35 technological fields, we selected all inventors with at least one patent in one the following technological fields: 11) Analysis of biological materials, 13) Medical technology, 14) Organic fine chemistry, 15) Biotechnology and 16) Pharmaceutical.

we need to retrieve their patents independently of their technological content. To this end, we first assign a unique identification code to each inventor following the disambiguation methodology described in Pezzoni et al. (2014). We then select all the patents that are classified in a pharmaceutical field. Finally, we take the list of identification codes (i.e., unique inventors) corresponding to those patents and retrieve all the patents that have been assigned to those codes, even though some may be classified in other technological fields. To assess the quality of the disambiguation process and our ability to track inventors' careers, we select all inventors working for a target group — a sample of 50,529 'not-processed' inventors (i.e., prior to applying the disambiguation process of Pezzoni et al. (2014)) — and match them with LinkedIn data. The results, presented in Appendix A, show that, on the one hand, our disambiguation process is fairly accurate compared to previous findings (Ge et al., 2015), and on the other hand, the remaining errors in classifying inventors' statuses appear to be randomly distributed, suggesting they do not introduce systematic bias into our results.

Our initial dataset refers to more than nine hundred thousand patents over the period 1978–2015, with over a million scientists listed as authors. The data retrieved from PatStat include the applicant's name (i.e. the company that applies for the patent), the date of the first application (i.e. priority patent), the name and full address of the inventors of the patent, information about the patent class, and the number of citations made and received.

Step II: Identification of Original Applicant. EPO data provide the list of applicants: company, institution or other legal entity that owns the patents. Several factors render this list unsuitable for use in its raw form. First, the PatStat dataset shows the last owner in time, which could include the company that bought the patent from the original applicant. However, we are interested in the name of the first applicant, as this is the actual employers of the inventors at the time of the application. Second, as there are patents that report more than one applicant, it is necessary to assign all inventors listed in a patent document to their corresponding applicant, what is generally known as the 'affiliation issue'. Finally, the PatStat dataset does not provide a consistent identification number for applicants over time that we can use to tell whether an inventor moves to a new company, which is crucial for our investigation. As explained below, substantial effort has been invested in addressing these three issues.

To identify the *original applicant*, we use two different sources of information. First, we retrieve the name of the original applicant from the Patent Register dataset, an EPO dataset directly connected to PatStat, which contains all the publicly available procedural information on patent applications, including the name of all applicants and any changes over time, as the patents progress through each stage of the granting process. Second, for each European patent, we use the information on applicants reported in the first application if a priority was claimed. Combining these two pieces of information, we can retrieve the original applicant for all the selected patents. Around 4 % of patents are affected by this change.

Step III. Identification of Pharma Groups. Finally, we create a dynamic group identification code (i.e. ID group) to link all applicants that belong to the same mother company using the following procedure. First, based on the semantic similarity of the applicant's name and address, we define a unique identification code at the firm level, which cannot change over time. In this first step, we devote considerable attention to minimise false positives, i.e., two applicants being erroneously assigned the same identification code. Second, we match the name and country of these firms with those we retrieved in the BvD datasets (Orbis and Zephyr), by using semantic matching and then manually checking thousands of firms that were left unmatched. After each firm is assigned to a unique company in the BvD datasets, we use the information on group structure in Orbis, as well as the wealth of information available online, to assign an initial ID group for the first year that firm is observed in our data, which for most of the firms is 1988. The ID group aggregates all the firms that belong to the same mother company. Whereas the identification code at the firm level is fixed, the ID group assigned to a firm can change over time depending on mergers, acquisitions and spin-offs. By carefully constructing the ID group at each point in time, we can follow an inventor's career and decide whether she has indeed moved to a new employer or continues to work for the same mother company.[22] Third, we verify the quality of our group classification using a recursive algorithm that identifies all large movements of inventors from one group to another. More precisely, we look at all movements of 10 or more inventors between two groups and check that these are not explained by a deal that we failed to feed into our dynamic ID group or due to another mistake in our group classification. Once a group-level identification code has been assigned to each firm in a given year, we can use the patent data to track the careers of inventors. Note that we use the terms 'firm' and 'company' interchangeably to refer to entities or group of entities (e.g., Pfizer Ltd UK and Pfizer Inc US) belonging to the same industrial group.

Step IV. Affiliation issue. The main objective of this step is to ensure that each inventor is associated with only one group in a given year. In the data, we may observe cases where the same inventor appears on different patents within the same year, applied for by different groups, or conversely, cases where a single patent lists multiple applicant groups. To address these situations and assign each inventor to one and only one group (i.e., resolve the *affiliation issue*), we define specific assignment rules based on a careful analysis of inventors' career trajectories. For example, suppose a patent lists three inventors and two applicants, A and B. If one of these inventors has previously applied for a patent with applicant A, we assign A (rather than B) as the applicant for this new patent. More generally, we apply *conservative* rules designed to minimize the number of employer changes in an inventor's career history.

At the end of this process, our analytical dataset includes the 311,358 inventors with patents in at least two different years,[23] resulting in a total of 1000,751 inventor x year observations over the period 1988 – 2015, equivalent to 3,21 observations for inventor

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[22] Consider, for instance, the acquisition of Pharmacia Corp by Pfizer in 2002. Assume that we observe two inventors. Inventor *i* has a first patent in 1998 with Pharmacia, and then a second patent in 2003 with Pfizer. Inventor *j* also has a first patent in 1998 with Pharmacia and a second patent in 2003 with Novartis. Our dynamic ID group will tell us that, in spite of both having two patents with two different applicants, the first inventor has not changed employer, because Pharmacia no longer existed in 2003 as it was acquired by Pfizer.

[23] The distribution of patents per inventor is positively skewed, with the majority of inventors named on a single patent and a right tail of highly productive inventors. The final dataset corresponds to the 25,9% of initial inventor population.

on average. For each inventor, we observe the number of patents, with their technological classification and the number of citations received, the firm they work for and whether their firms are object of an acquisition.

3.2. M&As deals

M&As that occurred during the period 1988–2015 are retrieved from Zephyr dataset published by BvD. As detailed in Table 1, our final sample comprises 513 acquisition deals involving firms active in the pharmaceutical sector worldwide. We only consider outright acquisitions. We exclude partial acquisitions, and in the few cases where the deal is classified as a merger of equals, we designate as acquired firms those identified in the "target" column by Zephyr. To account for the diversity in acquisition values, we introduce a dummy variable, Big, indicating whether the acquisition value exceeds 5 billion euros at the time of the transaction. This criterion is met for 63 deals, corresponding to about 12 percent of all acquisitions in our sample. Distinguishing between small and large transactions is particularly relevant in the context of merger control, given the growing concern over stealth acquisitions—transactions deliberately structured to fall below reporting thresholds and thus avoid antitrust review (Wollmann, 2019)

Fig. 2 illustrates the temporal distribution of these transactions. The black line shows the annual count of acquisitions on the right-hand side axis, and the histogram indicates the corresponding values on the left-hand side axis. From the year 2000 onward, the number of acquisitions tend to oscillate around 30 deals per year, with a peak of 48 in 2007. Looking at the values, we observe two distinct peaks in year 2000, driven by Glaxo-SmithKline and Pfizer-Warner Lamber deals, and in 2015, influenced by the Actavis-Allergan and Pfizer-Hospira transactions. The variability in the value of these acquisitions is considerable and only partially correlated with the quantity of deals executed.

3.3. Inventors' status

As already mentioned, we cannot track inventors at all points in time because we have no information about their status in the time window between two observations (i.e. patents) or after the last patent observed. To obtain the most complete information on inventors' activity, we rely on all available patent applications rather than focusing exclusively on patents that are granted.

For each observation (patent-year), we categorize inventors into one of two statuses – *Stay* or *Leave* – based on their employer in the subsequent observation. The status *Stay* is assigned to an inventor who files a patent in year t if the applicant on her next patent, filed in year $t + x$, belongs to the same group she works for at time t. An inventor is assigned the status *Leave* at time t if her patent at $t + x$ is filed by a different group from the first patent. Finally, if the patent observed in year t is the last observation available, t^l, the inventor is assigned the status *Exit*. Note that the patent history of all inventors ends with an *Exit*. Starting from this classification, we add information on any acquisitions that occur after observation at time t and before next observation at $t + x$.

To clarify how our classification works, Fig. 3 shows the case of an inventor observed four times between 1990 (first patent) and 1997 (last patent). In every year she patents, we can classify her status by comparing the employers in two 'consecutive' observations and noting whether an acquisition has occurred in the interval between these two observations. This inventor patents in 1990 with group *A*, but at the following available observation (patent 2) in 1992, she works for group *B*. As *A* is not involved in any acquisition, we assign the status *Leave*, indicating that she leaves group *A*. We assign her the status *Stay* for her second patent because she still works for *B* by the time of patent 3 in 1995. Next, we assign the inventor the status *Stay_T* at patent 3 (where the suffice T means Target), because, although in 1997 she works for a new firm, our dataset shows that firm *C* acquired firm *B* in 1996. Finally, her status is *Exit* from 1997 onwards, for no other observations are available.

Table 2 presents the distribution of observations across the three possible statuses: *Stay, Leave*, and *Exit*. It also distinguishes cases where inventors in the Stay and Leave categories are observed after an acquisition (i.e., *Stay_T* and *Leave_T*). The analytical sample used to study stayers and leavers consists of 760,047 observations, while the sample for examining the relationship between exit and target firms includes 240,704 inventor observations. We note that the classification of *Exit_T*, which captures inventors exiting after an acquisition, depends on the number of years since their first patent and the time window after their last observed patent. Further details on its construction are provided in Section 4.1 and Appendix B.

One key insight from Table 2 is that among inventors in target firms, 27.4 percent leave after an acquisition, while 72.6 percent remain with the firm. In contrast, the proportion of inventors who leave in non-target firms is significantly lower (14.3 %), with the vast majority (85.7 %) staying. These descriptive statistics suggests a higher likelihood of inventors' turnover in firms involved in acquisitions compared to those that are not: a relationship that will be explored in more detail in the econometric analysis in Section 4.

3.4. Variables and descriptive statistics

For each inventor, we use the patent data to derive individual and firm-level variables. Starting with the individual variables, we compute an inventor's *experience* and *inactivity* at time t by counting, respectively, the number of years since their first patent and the years since the previous patent, which may or may not coincide with the first patent. *Productivity* in year t is measured as the ratio of the number of patents to years of experience. We adopt two distinct criteria for counting patents, resulting in two productivity measures: the cumulative number of patents and the cumulative number of patents over the last five years. For this latter measure, following

Table 1

Mergers and Acquisitions. This table presents descriptive statistics of the transaction values of the 513 acquisitions we have analysed. Sixty-three acquisitions, accounting for 12.3 % of the total deals, have a value in excess of €5 billion, and they are classified as 'Big'.

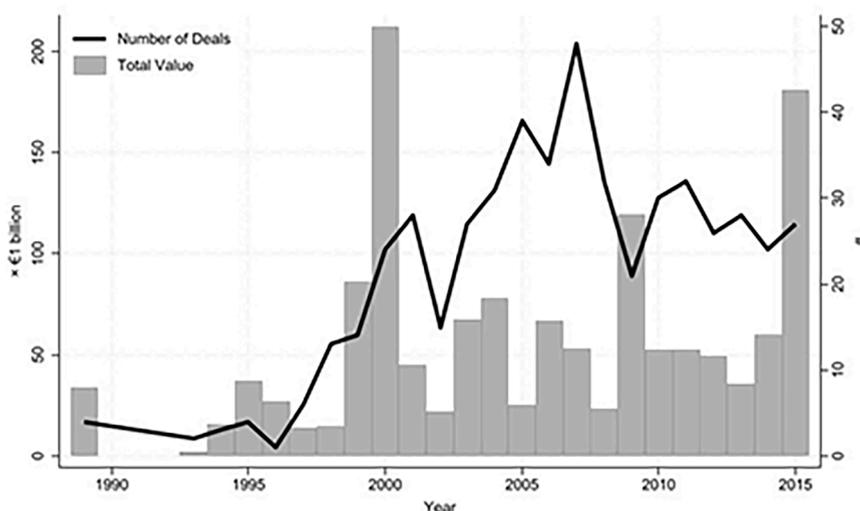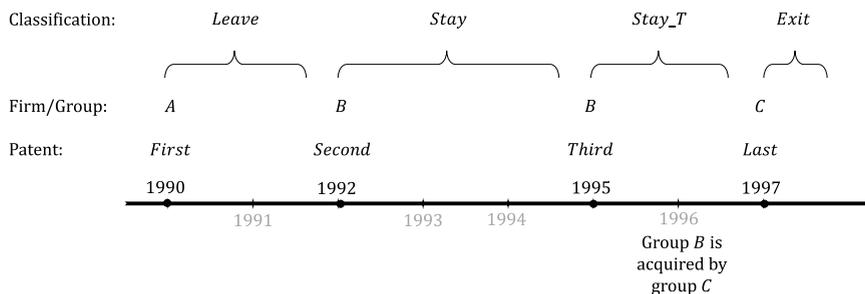| Variable	#Deals (%)	Mean	Std. Dev.	Min.	Max
Target Value	513 (100)	2679,925	8283,210	10,050	93,409,440
Target^{BIG} Value	63 (12,3)	17,161,133	17,749,976	5200,000	93,409,440

Fig. 2. Mergers and Acquisitions.

Fig. 3. Patents and Inventors Status.
Note: The figure shows the classification of inventor' status depending on whether she continues working for the same firm - *Stay* - or moves to another firm - *Leave*. We use the suffix *T* if the firm she works for is the target of an acquisition. The status of all inventors is recorded as *Exit* in correspondence of the last patent.

Trajtenberg (1990), we also compute a quality-adjusted measure by counting the number of patents over the last five years along with the citations they have received in a 5-year window. For each inventor, we also create a set of technological dummies, based on the technological classes in the IPC classification of their patents,[24] which can control for the inventors' specialization in specific technologies.[25] Finally, for firm-level variable, we also compute the cumulative number of patents for the target group, which is used as a proxy for the group's size. This variable is added as control when estimating exit rates and separation rates, and it is also used to select inventors in the control group (see Appendix B).

Table 3 presents basic descriptive statistics for the variables described above, distinguishing between the data used to estimate the exit rate (top panel) and the separation rate (bottom panel).

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[24] A dummy variable for an IPC class is set to 1 if the inventor has at least one patent classified in that class. If a patent is classified in multiple IPC classes, as frequently occurs, all the corresponding technological dummies will be set to 1.

[25] In a recent work, Tzabbar et al. (2022) examine how technological specialization, specifically the inventor's ability to connect diverse technologies, contributes to lowering the likelihood of leaving a company.

Table 2

Distribution of Inventors by Status.

This table presents the distribution observations among the three inventors' status: *Stay*, *Leave* and *Exit*. For *Stay* and *Exit*, we report the number of observations where inventors are employed by a firm that is the target of an acquisition, as well as cases where they are not. All inventors are classified as *Exit* in correspondence of their last observed patent. The classification of *Exit_T* (Exit after a Target) depends on the number of years after the first patent (w) and the time window after the last patent (v) – see Section 4.1 and Appendix B. When studying exit rates, we check robustness of results for alternative values of w and v.

#Obs (%)	Target	Non-Target
Leave	2675 (27.4)	107001 (14.3)
Stay	7104 (72.6)	643267 (85.7)
Leave + Stay	9779 (100)	750268 (100)
	All Firms	
Exit	2,40,704	

Table 3

Descriptive Statistics.

This table presents descriptive statistics for the covariates used to estimate exit rates (Eq. (1)) and separation rates (Eq. (2)), shown in the top and bottom panels, respectively. The number of observations in the top panel matches those in Tables 4 and 5, while the number of observations in the bottom panel corresponds to those reported in Table 6.

Variable	#Obs	Mean	Std. Dev.	Min.	Max
Exit - Eq. (1)					
Target	2,40,704	0.014	0.118	0	1
Target Big	2,40,704	0.009	0.093	0	1
Inactivtity	2,40,704	2.326	1.708	0	5
Five-Year Productivity	2,40,704	0.759	0.920	0.200	62.9
Year first patent	2,40,704	1999	5.621	1985	2007
Leave - Eq. (2)					
Leave	760,047	0.144	0.351	0	1
Target	760,047	0.013	0.113	0	1
Target Big	760,047	0.008	0.087	0	1
Experience	760,047	4.632	4.899	1	37
Five-Year Productivity (patents)	760,047	1.070	1.836	0.200	118.8
Five-Year Productivity (weighted patents)	760,047	1.698	4.083	0.200	236.8
Group patent	760,047	202.1	311.5	1	1669

4. Empirical model

In this section, we describe the empirical models used to evaluate changes in scientists' exit rates and separation rates around the period of a merger, as well as the strategy used to quantify what these movements mean in terms of forgone patent (for inventors that exit the dataset) or changes in productivity (for inventors that move to a new group).

4.1. Exit rate

Our empirical strategy to investigate the relationship between acquisitions and the probability of exit begins by defining a reference year to classify each inventor in the category "*exit*" or "*alive*", and then identifying whether the firm they work for is the target of an acquisition in a time window before that reference year.

Before explaining the empirical model used to study exit rates, we introduce the following notation. Each inventor is observed in at least two time periods: the year of the first patent and the year of the last patent, denoted by t^f and t^ℓ, respectively - i.e. $t = \{t^f,...,t^\ell\}$. Some inventors are also observed in other periods between these two, which we denote with t^x.

As explained in Section 3, all inventors are assigned the status *Exit* at the time of their last patent. To create a meaningful exit indicator, E, we evaluate whether a scientist is still active w years after their first patent. Consider the example in Fig. 4, which shows the timeline of two inventors with the same year of the first patent, t^f, but two different years of their last patent, t^ℓ. For a specific w,
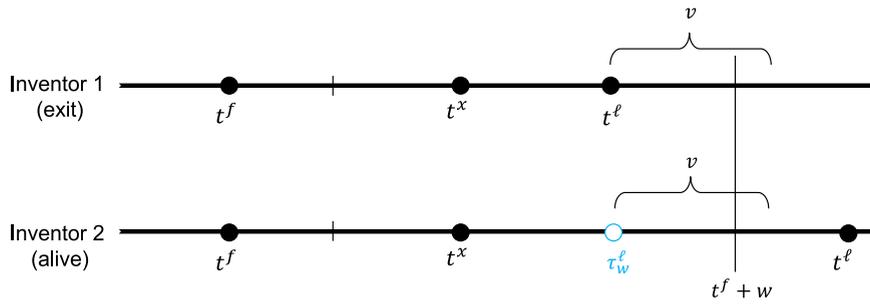
Fig. 4. Timeline of Patent Activity: Exit and Alive.
Note: A black dot on the timeline indicates that the inventor applies for a patent in that year. A bar indicates a year where the inventor has no patents. The figure shows two inventors with the same year of first patent, t^f, but different years of last patent, t^ℓ. The vertical dash line indicates the time $t^f + w$ when we evaluate the inventors' status: Inventor 1 (respectively, 2) is assigned the status *exit* (respectively, *alive*) since her last patent is before (respectively, after) the vertical line. The time v is used to evaluate whether a merger takes place around the year of the last observed patent, t^ℓ in the case of exit or the year of the last "imputed" patent, τ_w^ℓ for inventors alive. In the empirical analysis we check robustness of our results for two different values of w and v, namely $w = \{5, 10\}$ and $v = \{2, 5\}$. Note that, at the time $t^f + w$ when we evaluate the inventors' status, the years of inactivity for inventor 1 are $(t^f + w - t^\ell)$, whereas for inventor 2 they are $(t^f + w - t^x)$.

inventor 1 is assigned the status *Exit* ($E^w = 1$), since the year of the last patent is before $t^f + w$ (the vertical dashed line). Inventor 2 is classified as (productively) *alive* ($E^w = 0$), meanwhile, because she has a patent after w years since her first patent.

The treatment T^v refers to the fact that an inventor works for a pharmaceutical firm that is the object of an acquisition. We construct this variable using the set of inventors classified in the exit category (i.e. $E^w = 1$) and verifying whether their companies have been the target of an acquisition in a time window v after their last patent (hence the superscript v).

In other words, using the terminology of Section 3.3, an inventor is assigned the status *Exit_T* if *(i)* the company she works for at the time of her last patent, is acquired and *(ii)* the acquisition takes place within a time window v since t^ℓ. In Section 5, we will check the sensitivity of our results for two different values of w and v, namely $w = \{5, 10\}$ and $v = \{2, 5\}$.[26]

Note that the definition of the treatment variable generated for *exit* group cannot be used for inventors that are alive, as this would imply that the treatment takes place after the outcome of interest. For these inventors, we need to choose a reasonable time window in which to evaluate whether their employers have been the object of an acquisition. To this end, we assign each active inventor a 'hypothetical' last year, τ_w^ℓ, randomly drawn from a distribution equivalent to the observed distribution of t^ℓ for inventors in the *exit* group We do this by considering the first year of patenting t^f, as inventors who started producing patents earlier in the data sample period are more likely to be observed for more years than those who started later. By way of example, inventor 2 in Fig. 4 has been assigned a hypothetical last year τ_w^ℓ similar to inventor 1's last year t^ℓ. Note that, in the case of inventor 2, we then check if the last company she works for before τ_w^ℓ, has been the object of an acquisition.

After constructing the dependent variable, E^w (i.e. whether an inventor exits the innovation market or she is still alive) and the treatment dummy, T^v, (i.e. whether her company is the target of an acquisition) we define the following empirical model for any inventor i working for company c:

$$Pr\left(E_{i,c}^w = 1 | T_c^v, \mathbf{X}_{i,c}\right) = G\left(\beta T_c^v + \Gamma \mathbf{X}_{i,c} + \delta_c\right), \tag{1}$$

where $\mathbf{X}_{i,c}$ refers to a set of control variables for inventor i or her company c that can affect the probability of exit, namely: the year of the first patent (i.e. inventor's cohort), years of inactivity (i.e. number of years since the inventor last applied for a patent)[27] and her productivity, measured by the cumulative number of patents at the time of the merger; and, finally, the number of patents assigned to the company, as the exit rate may vary depending on an employer's size. Eq (1) also includes firm-fixed effects, δ_c to control for unobservable heterogeneity related to company culture and managers' strategic approach to consolidations. Finally, we also estimate a specification that includes 26 technological fixed effects, to account for differences in inventors' area of specialisation. The inclusion of all these control variables effectively helps us to estimate whether the probability of exit for inventors of target firms is significantly

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[26] We chose these values because 5 and 10 years correspond, respectively, to $p(50)$ and $p(80)$ of the distribution of time between first patent and last patent, $(t^\ell - t^f)$ for all inventors in our dataset. Consider an inventor i with her first patent in 2000 and last patent in 2009. Given that 2009 > 2000 + 5 but 2009 ≤ 2000 + 10 , she will be classified as active ($E^w = 0$) for the short window $w = 5$ but as exiting ($E^w = 1$) for $w = 10$. This example shows that the choice of two different time windows allow us to check robustness of results. Note also that since our patent data extend until 2015, the analysis includes only inventors whose first patent was published in 2010 or earlier when $w = 5$, and those with a first patent published in 2005 or earlier when $w = 10$.
[27] In the analysis of separation rate (Section 4.2), we use experience (defined as the number of years since the first patent) to control for changes over the career-cycle. Here we use years of inactivity instead, for the status *exit* or *alive* are evaluated exactly w years after the first patent, which implies that all inventors have the same experience.

different than that of inventors with the same observable characteristics, working on similar technologies for firms of similar size but which have not been the object of an acquisition.

Eq. (1) is estimated using both probit regression (under the assumption that the conditional probability G takes the normal form) and a linear probability model. The coefficient of interest β provides us with the estimated increase in the probability of observing an exit for scientists that work in a target firm ($T = 1$), compared to a baseline group of scientists working in firms that are not targets of an acquisition ($T = 0$). In Section 5, we also estimate a specification with a second treatment dummy T^{BIG} taking value 1 for deals above €5 billion,[28] which allows us to examine whether exit rates differ depending on the size of the target company. Additionally, to investigate whether there are statistically significant differences in exit rates across inventors of different stature, we interact different measures of productivity with the treatment variable T.

Given that the classification of inventors in the *exit* group is based on patent data up to 2015, it is possible that inventors who apply for their first patent towards the end of the sample period,[29] might be inaccurately classified due to right censoring. This measurement error in the dependent variable introduces a second error term, alongside the standard residual, potentially resulting in a larger error variance. If the right-censoring problem is not systematically related to the treatment T, the OLS estimator remains consistent, although standard errors might be larger than if the true status of the inventor could be accurately observed. Conversely, if patent applications covering the discoveries of targets' scientists are consistently delayed in the aftermath of a consolidation, the likelihood of erroneously classifying an inventor in the *exit* group may be higher for the treated group. This situation could lead to a negative correlation between T and the error term. In such a scenario, Ordinary Least Squares (OLS) estimates would exhibit a downward bias, implying that our findings may represent a conservative lower bound. In Section 5, we demonstrate that the results remain qualitatively similar even when using different time windows to classify inventors as part of the *exit* group.

4.2. Separation rate

To study the relationship between mergers and the *separation rate*, i.e. the probability that inventors move to another company, we first classify each inventor in every observed period of patent activity as either leaving ($L = 1$) or *not leaving* her employer ($L = 0$) and then check whether the firm she works for is the object of an acquisition ($T = 1$) or not ($T = 0$). In other words, we have $T = 1$ for inventors that are classified as *Leave_T* or *Stay_T* according to the taxonomy used in Section 3.3.

The variable L and T are used to estimate the following linear probability model:

$$P\big(L_{i,c,t} = 1 \mid T_c, \boldsymbol{X}_{i,c,t}\big) = \beta T_c + \Gamma \boldsymbol{X}_{i,c,t} + \delta_i + \delta_t + u_{i,c,t} \tag{2}$$

where $\boldsymbol{X}$ is a set of inventor-level or company-specific controls described below, δ_i indicates inventor fixed effects, δ_t indicates times fixed effects and u is the error term. Despite extensive efforts to address the challenges associated with determining inventors' names and affiliations, there remains a possibility of misclassification in the "stay" or "leave" status of certain inventors. Similar to the exit model, this measurement error in the dependent variable may contribute to a higher standard error in our OLS estimates.

One important difference between the dataset used to investigating separation rates and the one used for exit rates is that an inventor can exit the dataset only once, but she can move to a new company more than once. Indeed, every time an inventor applies for a new patent, we can tell whether she is staying with the same employer or has moved to a new one, as shown in the example in Fig. 3. Accordingly, whereas Eq. (1) is estimated using only one observation per inventor, Eq. (2) has a time subscript because we use '$n_i - 1$' observations per inventor, where n_i indicates the number of times inventor i applies for a patent (i.e. the observed years of productivity).[30] This explains why, for specification (2), we can include inventor fixed effects δ_i. The set of controls $\boldsymbol{X}$ is also adjusted to accommodate for the fact that we have now multiple observations for the same inventor. Concretely, $\boldsymbol{X}$ now includes not only inventors' cohort (year of first patent),[31] their productivity (cumulative number of patents) and the number of patents assigned to their firms, but also scientists' experience (number of years since the first patent) to control for life-cycle effects. Finally, as for Eq. (1), we also estimate a specification that includes technological fixed effects, to account for differences in inventors' area of specialisation.

A prerequisite for establishing a causal link between acquisitions and job separation would be to know with certainty that an acquisition is announced before an inventor leaves. However, the nature of our data, where an inventor is observed only when she files a patent, does not allow us to observe the exact date an inventor moves to a new company, and therefore we do not know whether a departure happens before or after a deal. To clarify the nature of the problem, Fig. 5 shows the case of an inventor observed in four periods $t = \{t^f, t^{x_1}, t^{x_2}, t^\ell\}$. We know that in period t^{x_1} the inventor works for company A and that in period t^{x_2} she works for company B. Additionally, we know that company A was acquired at time t^T by another firm C. However, we cannot observe whether the inventor leaves firm A between $[t^{x_1}, t^T]$ or between $(t^T, t^{x_2}]$. And even if we could observe the exact date of departure, and this day falls after the announcement date of the merger, it would still be difficult to affirm without the shadow of a doubt that the inventor would have not left firm A had the merger not taken place. Given this intrinsic limitation of patent data, the coefficient β in Eq. 2/> cannot be

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[28] This corresponds to the top 75 deals in our dataset, though results are very robust to the use of other thresholds. We note that the dummy T^{Big} includes the largest mergers of equals, such as AstraZeneca or GlaxoSmithKline.

[29] Note that when $w = 5$, only inventors whose first patent was published in 2010 or earlier are included in the analysis, whereas when $w = 10$, only those with a first patent published in 2005 or earlier are considered.

[30] Specifically, we do not use the last observation because all inventors are classified as "exiter" when they apply for their last patent.

[31] Of course, the cohort dummies are included only when inventor fixed effects are not included in Eq. (2).
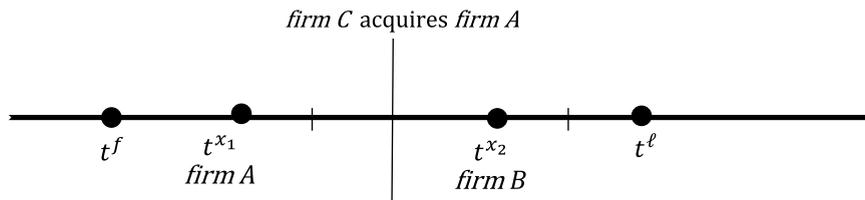
firm C acquires firm A

Fig. 5. Timeline of Patent Activity Inventors' Affiliation.

Note: The figure shows the timeline of an inventor's patent activity and her affiliation. A black dot on the timeline indicates that the inventor applies for a patent in that year. A bar indicates a year where the inventor has no patents. The vertical dash line indicates the year firm A is acquired by another firm C. The inventor moves from firm A to firm B sometimes between t^{x_1} and t^{x_2}. Firm A is acquired during this time window. period, but we cannot tell whether the inventor moves from A to B before or after firm A is acquired.

interpreted as a causal effect of mergers on separation rates. However, by controlling for other characteristics that can affect the probability that a scientist moves to another company, our analysis provides relevant evidence on how inventors' separation rates change when, in the spell between two patents (in this example, one at time t^{x_1} and the other at time t^{x_2}), their employer is the target of an acquisition ($T = 1$) compared to the case where their employer is not a target ($T = 0$).

4.3. Patent output for stay, leave and exit

One important contribution of our study is to provide novel evidence on the number of "lost patents" associated with any increase in the exit rate and changes in productivity for inventors who leave and those who stay. Specifically, for leavers and stayers, we estimate the change in patent output by comparing their post-acquisition patent counts (where, for leavers, this refers to patents produced in their new labs) to those of a control group of scientists who neither relocate nor work for firms targeted by acquisitions. For *exiters*, who by definition do not produce any future patents, the productivity loss is estimated instead by simply counting the number of patents of a control group of active inventors.

Our identification strategy rests on the idea that, if we can find two inventors that are not statistically observationally different from each other before the onset of a consolidation, then we can assume that their productivity would have been similar in the following period too. The construction of the control groups is based on a "coarsened exact matching" technique detailed in Appendix B, similar in spirit to the approach by Azoulay et al. (2010). Concretely, for each treated inventor in the exit analysis, we first select control scientists not affected by a merger with the *same* cohort (year of the first patent), *same* inactivity (years since the last patent) and *same* productivity (total number of patents over the last five years) and then select, among the controls that satisfy these three conditions, the two inventors whose firms have a number of patents similar, but not necessarily identical, to the target firm (*nearest-neighbour* matching). Matching treated and control groups based on the size of their employers' patent pool mitigates also possible concerns that treated inventors may move to firms with varying propensities to patent.

The same matching procedure is used to study change in patent output of stayers and leavers, with the only difference that the exact matching is not done on inactivity but on experience (see footnote 28). A detailed explanation of the construction of the control group is provided in Appendix B.

One significant advantage of inventor-level studies compared to firm-level works is that the "donor pool" used to construct the counterfactual consists of thousands of inventors, which makes it easier for each treated inventor to find controls that are observationally equivalent. We note that the exact matching on cohort and experience allow us to control for life-cycle and period effects, as in other studies on scientific productivity. We also note that, whereas inventors can exit the dataset only once, a small number of inventors are classified as *Leave_T* and *Stay_T* more than once (see Appendix B for details). The matching procedure above is applied each time an inventor is classified as *Leave_T* and *Stay_T* but results are robust to dropping these cases from the dataset.

Of course, we cannot rule out the possibility that there can be optimal inventor selection based on characteristics we cannot observe. For instance, managers in charge of consolidating the research activities may choose to retain their most talented inventors while asking those working on projects that are less promising to either leave the company or to move to a non-research role within the organisation. If this is the case, our results based on matching on observables may overestimate the patent loss due to exit, and the productivity decline of leavers, while potentially underestimating the reduction in patent output for stayers. However, we argue that research is characterised by a level of uncertainty that the observable inventors' patent history is the best predictor of their future productivity and thus very informative on any unobserved selection mechanism. Indeed, results in Section 5 show that the probability of exit and separation does not differ between inventors of different stature. For instance, the fact that top inventors are equally likely to exit as other inventors suggests that our treated group is unlikely to include predominantly scientists who would have not produced any patents even in the absence of the merger.

5. Results

This section presents first the estimated exit rate and separation rate for inventors of target firms and then evaluate the patent loss for exiters or change in patent output for leavers and stayers.

5.1. Exit rates and separation rates

Table 4 presents the results for the *exit rate* when we define (i) the exit or alive status five years after the first patent (i.e. $w = 5$) and (ii) the treatment status using a time window of two years (i.e. $v = 2$). Table 5 below presents a robustness check for different values of w and v (specifically, $w=\{5,10\}$ and $v=\{2,5\}$), showing that the results remain consistent.

We start by noting that the outcomes obtained using probit and the linear probability model (LPM) are quantitatively very similar and that the *R-squared* for the LPM indicates that our model can explain a significant part of the variation in exit rates. Three compelling findings emerge from the estimated coefficients. First, the probability of exit among scientists working for targets is between 7.6 and 11.5 percent higher compared to other scientists whose employers are not the object of acquisitions.[32] These results are robust to adding an increasing number of covariates, including a set of technological dummies to control for the areas of specialisation of the inventors.

Second, the coefficient on dummy *Target*[BIG] shows that exit rates are similar for large and small deals. This means that our results are not driven by an unusually large proportion of exit for deals where targets have a market value above €5 billion.

Third, looking at the coefficient on *Productivity* in columns (3) and (4), inventors in the top quintile for number of cumulative patents over the last five years are 18.2 percent less likely to exit (i.e. to be no longer observed) five years after their first patent, compared to their less productive peers. However, these highly productive scientists experience an increase in the likelihood of exit of around 22 percent during the period of an acquisition, which means that they are equally (or even more) likely to exit the innovation market. Finally, to check robustness of results to the heterogeneity in patents quality, columns (5) and (6) show that similar results are obtained when the set of more productive inventors is identified using the number of patents over the last five years, adjusted by number of citations received in the following five years after the first application.

The significant rise in the probability of exit for all scientists of targets, irrespective of their standing within the organizations, has important implications for both the firms and the society. From a corporate perspective, this serves as a stark cautionary signal: while acquirers try to retain their most productive inventors and potentially shed those engaged in less promising projects, there is no evidence supporting their ability to achieve this optimal scientists' selection. On a societal level, the escalating rate of exits may come at a considerable cost in terms of both quantity and quality of patents lost, an aspect that we explore further below.

In Table 5 we check the sensitivity of our results to changes in the two time-windows, w and v, used to define, respectively, the dependent variable *Exit* and the dummy *Target*. Columns (1) and (2) are the same as columns (3) and (4) of Table 4 for ease of comparison. The estimated coefficients on *Target* show that the probability of exit increases substantially across all values of w and v, with 7.6 percent reported in Table 4 being a lower bound of such probability. As expected, the probability of exit rises significantly when we use the time window $v = 5$ to evaluate whether a firm has been object of an acquisitions, reaching a value of 17 percent. The results for the interaction term *Productivity x Target* confirm that highly productive inventors, who are normally 10 to 17 percent less likely to stop patenting, experience an increase in the likelihood of exit that completely compensates for their initially lower base-rate probability.

Table 6 reports the results for *separation rates*. The *R-squared* value in column (1) and (2) indicates that our specification once again has a good fit and can explain around 20 % of the variation in the dependent variable. The coefficients in the first row show that inventors of targets are 12 to 19 percentage points more likely to move to another firm than those who work for non-targets. Columns (3) - (6) show that results are very robust when we include inventor fixed effects in addition to the time-varying control variables. Our results closely mirror those by Verginer et al. (2025), who find a 13.5 % higher probability of departure for inventors of targets. This similarity is particularly noteworthy considering the difference in estimation techniques and number of observations.

Interestingly, columns (4) and (6) show that the departure rate is 3.5 percent lower for large targets compared to small targets. This may be due to the tendency of large companies, upon acquiring the research activities of a relatively small lab, to prioritize investments in the *D stage*, rather than the *R stage*.

The coefficients on *Productivity* and the interaction terms *Productivity* x *Target* are small and often not statistically significant. This suggests that, as far as the departure rates are concerned, there are only marginal differences between inventors of different stature, whether they work for targets or other firms. Lastly, we note that results are similar whether we identify the highly productive inventors using the number of patents over the last five years - columns (3) and (4) – or the number of patents adjusted by number of citations – columns (5) and (6).

5.2. Change in inventors' patent output

In this section, we provide inventor-level estimates of the number of patents lost for inventors with status *Exit_T* as well as the change in patent output associated with *Leave_T* and *Stay_T*. To this aim, for each (treated) inventor with status *Exit_T, Leave_T* and *Stay_T*, we select (control) inventors using the matching algorithm detailed in Appendix B.[33]

Starting with a definition of *exit* based on a time window of five years after the first patent (i.e. $w = 5$), the results in Panel A of Table 7 indicate a loss, on average, of around 2 patents (respectively, around 3 patents) over a period of 3 years (respectively, 5 years)

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[32] These estimates are comparable to those reported in other studies. Verginer et al. (2025), for instance, find that an increase of 6.3 percent in the number of inventors who no longer apply for patents. Cunningham et al. (2021) find that "only 22 percent of pre-acquisition inventors move to the acquirer after the acquisition, while 78 percent move to other firms", which seems improbably high.

[33] The results presented in Tables 7 to 9 below remain robust when acquisitions occurring after 2010 are excluded.

Table 4

Exit Rates.

This table presents the likelihood of exit of inventors estimated using a probit model or linear probability model (LPM). For the probit model, the numbers in columns (1) and (2) are the marginal effects. The dependent variable is a dummy indicating whether inventor i is no longer observed in the dataset ($Exit = 1$) w years after the first patent. The independent variable $Target$ indicates whether the inventor's firm is a target of an acquisition v years after the inventor's last patent. $Target^{BIG}$ indicates a whether the value paid for the target is above €5 billion. In this table, we use $w = 5$ and $v = 2$; robustness checks for different values of w and v are shown in Table In columns (3) and (4) $Productivity$ is a dummy taking a value of 1 for inventors in the top quintile for total number of patents over the last five years. In columns (5) and (6), $Productivity$ is a dummy taking a value of 1 for inventors in the top quintile for total number of patents adjusted by number of citations. The interaction $Productivity$ x $Target$ is "active" when the firm of the highly productive inventor is the target. All specifications include a complete set of dummies indicating the inventors' cohort (i.e. the year they apply for their first patent), inventors' years of inactivity (divided into three groups: one year of inactivity, between 2 and 3 years, or >3 years) and the size of the firms measured by the total number of patents they own. In the LPM of columns (3) to (6), we also add firm fixed effects and twenty-six different technological dummies to control for the area of specialization of the inventor. The coefficients for the probit model in columns (1) and (2) are the average marginal effects. The dataset includes one observation per inventor. Standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Probit (1)	Probit (2)	LPM (3)	LPM (4)	LPM (5)	LPM (6)
Target	0.115***	0.098***	0.086***	0.076***	0.097***	0.083***
	(0.026)	(0.031)	(0.020)	(0.028)	(0.021)	(0.030)
Target^{BIG}		0.028		0.016		0.021
		(0.048)		(0.038)		(0.040)
Productivity			−0.182***	−0.182***	−0.143***	−0.143***
			(0.004)	(0.004)	(0.005)	(0.005)
Productivity x Target			0.215***	0.222***	0.153***	0.172***
			(0.028)	(0.042)	(0.025)	(0.035)
Productivity x Target^{BIG}				−0.010		−0.030
				(0.054)		(0.048)
Cohort FE	Y	Y	Y	Y	Y	Y
Company FE			Y	Y	Y	Y
Inactivity	Y	Y	Y	Y	Y	Y
Firm Size	Y	Y	Y	Y	Y	Y
Technology Dummies			Y	Y	Y	Y
R-squared			0.232	0.232	0.226	0.226
#Obs	240704	240704	240704	240704	240704	240704

Table 5

Exit Rates – Sensitivity Analysis.

This table presents the likelihood of exit of inventors for different values of w - years after the first patent used to define $Exit$ – and v - the period around the last patent used to define whether a firm is a $Target$. Columns (1) and (2) are the same as columns (3) and (4) of Table.4

$Productivity$ is a dummy taking value 1 for inventors in the top quintile for total number of patents over the last five years. All specifications include a complete set of dummies indicating the inventors' cohort (i.e. the year they apply for their first patent), inventors' years of inactivity (divided in three groups when $w = 5$ and four groups when $w = 10$), the size of the firms measured by the total number of patents they own, firm fixed-effects and twenty-six different technological dummies to control for the area of specialization of the inventor. The dataset includes one observation per inventor. Standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	LPM $w = 5\ v = 2$ (1)	LPM $w = 5\ v = 2$ (2)	LPM $w = 5\ v = 5$ (3)	LPM $w = 5\ v = 5$ (4)	LPM $w = 10\ v = 2$ (5)	LPM $w = 10\ v = 2$ (6)	LPM $w = 10\ v = 5$ (7)	LPM $w = 10\ v = 5$ (8)
Target	0.086***	0.076***	0.175***	0.169***	0.081***	0.098***	0.139***	0.128***
	(0.020)	(0.028)	(0.018)	(0.023)	(0.013)	(0.021)	(0.014)	(0.021)
Target^{BIG}		0.016		0.011		−0.025		0.017
		(0.038)		(0.032)		(0.026)		(0.028)
Productivity	−0.182***	−0.182***	−0.182***	−0.182***	−0.116***	−0.116***	−0.117***	−0.117***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Productivity x Target	0.215***	0.222***	0.133***	0.134***	0.118***	0.099***	0.106***	0.107***
	(0.028)	(0.042)	(0.019)	(0.026)	(0.020)	(0.034)	(0.014)	(0.026)
Productivity x Target^{BIG}		−0.010		−0.003		0.027		−0.002
		(0.054)		(0.036)		(0.040)		(0.030)
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Company FE	Y	Y	Y	Y	Y	Y	Y	Y
Inactivity	Y	Y	Y	Y	Y	Y	Y	Y
Firm Size	Y	Y	Y	Y	Y	Y	Y	Y
Technology Dummies	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.232	0.232	0.234	0.234	0.362	0.362	0.364	0.364
#Obs	240704	240704	240704	240704	166932	166932	166932	166932

Table 6

Separation Rates.

This table shows the likelihood of separation of inventors estimated using linear probability model (LPM). The dependent variable is a dummy indicating whether inventor i leaves the firm she used to work for. Specifically *Leave* = 1 if the applicant (firm) of her "current" patent is different from the applicant of her previous patent. The independent variable *Target* indicates whether the inventor's firm is a target of an acquisition between her "current" patent and her previous patent. *Target*^{BIG} indicates a whether the value paid for the target is above €5 billion. In columns (1) - (4) *Productivity* is a dummy taking a value of 1 for inventors in the top quartile for total number of patents over the last five years. In columns (5) and (6), *Productivity* is a dummy taking a value of 1 for inventors in the top quartile for total number of patents adjusted by number of citations. The interaction *Productivity* x *Target* is "active" when the firm of the highly productive inventor is the target. Differently from the analysis of *Exit*, we now use a dataset with repeated observations for the same inventor. Specifications (1) and (2) include a complete set of dummies for Cohort FE (i.e., the year an inventor applies for their first patent), Year FE (the year of the patent) and Firm FE. Furthermore, all specifications include inventors' experience (number of years since first patent, linear and squared); the size of the firms measured by the total number of patents they own; and twenty-six different technological dummies to control for the area of specialization of the inventor. Some of the variables above are not included in the specifications when we include Inventor FE. Standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	LPM (1)	LPM (2)	LPM (3)	LPM (4)	LPM (5)	LPM (6)
Target	0.158***	0.189***	0.122***	0.141***	0.125***	0.146***
	(0.014)	(0.026)	(0.006)	(0.010)	(0.006)	(0.010)
Target^{BIG}		−0.051*		−0.034***		−0.035***
		(0.031)		(0.012)		(0.012)
Productivity	−0.041***	−0.041***	0.015***	0.015***	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Productivity x Target	−0.048***	−0.025	−0.021*	−0.003	−0.035***	−0.019
	(0.016)	(0.033)	(0.011)	(0.020)	(0.011)	(0.019)
Productivity x Target^{BIG}		−0.035		−0.029		−0.026
		(0.037)		(0.024)		(0.023)
Cohort FE	Y	Y				
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y				
Experience	Y	Y	Y	Y	Y	Y
Firm Size	Y	Y	Y	Y	Y	Y
Technology Dummies	Y	Y	Y	Y	Y	Y
Inventor FE			Y	Y	Y	Y
R-squared	0.195	0.195	0.033	0.033	0.034	0.034
#Obs	760047	760047	760047	760047	760047	760047

Table 7

Lost Patents for Exiters. This table presents an estimate of the number of lost patents associated with the exit of inventors of target firms. Each "treated" inventor of a target firm is matched with two "control" inventors of non-target firms using the algorithm explained in the Appendix B. Column (1) presents the mean cumulative number of patents over the five years before the *Exit* of "treated" inventors. Due to perfect matching, this variable is the same for treated and control inventors. Columns (2) and (3) show the number of patents produced by the matched (alive) control group in the following 3 yr and 5 yr after the Exit of treated inventors (who do not have any patent). Panel A uses $w = 5$ and $v = 2$ to define inventors' *Exit* status and firms' *Target* status. Panel B shows results for $w = 5$ and $v = 5$. Numbers in square brackets refer to 95 % confidence internal based on 1000 boostrap replications for the difference in the number of patents.

	#Obs	5 yr Cum Patents Before (1)	Cum Patents After 3 yr (2)	Cum Patents After 5 yr (3)
Panel A: w = 5 and v = 2				
Exit (Treated)	2453	4.12	0	0
Non-Exit (Control)	4906	4.24	2.14	3.07
			−2.14	−3.07
			[−2.23; - 2.06]	[−3.19; −2.94]
Panel B: w = 10 and v = 5				
Exit (Treated)	4898	3.19	0	0
Non-Exit (Control)	9796	3.97	1.86	2.69
			−1.86	−2.69
			[−1.91; −1.81]	[−2.78; −2.60]

for each exit associated to an acquisition. Given that, on average, these inventors have applied for 4 patents in the 5 years preceding their exit, this halt in patent output corresponds to a decrease ranging from 33 percent - i.e., 2.14/(2.14+4.24) - to 42 percent - i.e., 3.07/(3.07+4.24) - of the expected output that these scientists could have generated over their careers The results in Panel B show that we find very similar results when we look at exit ten years after the first patent.

Looking now at the inventors of targets that move to other labs, results in Table 8 show that they also suffer a decrease in their productivity of around 2 patents, compared to what they could have achieved in the absence of the acquisitions, counterfactual

Table 8

Change in Patent Output for Leavers.

This table shows the difference in number of patents between inventors that leave target firms and a control group. Each "treated" inventor of a target firm is matched with two "control" inventors of non-target firms using the algorithm explained in Appendix B. Column (1) presents the mean cumulative number of patents over the five years before "treated" inventors leave. Due to perfect matching, the variable is the same for treated and control inventors. Columns (2) and (3) show the number of patents produced by treated and control inventors in the following 3 yr and 5 yr, respectively. Numbers in square brackets refer to 95 % confidence internal based on 1000 bootstrap replications for the difference in number of patents.

	#Obs	5 yr Cum Patents Before (1)	Cum Patents After 3 yr (2)	Cum Patents After 5 yr (3)
Leaver (Treated)	2675	3.39	0.75	1.51
Non-Leaver (Control)	5350	3.40	2.71	3.72
			−1.96	−2.21
			[−2.10; −1.82]	[−2.41; −2.01]

constructed by selecting inventors that do not move. Note that, differently from the results in Table 7 where the treated inventors stop patenting, the results in Table 8 show the difference in patenting between the observed number of patents of the (treated) leavers and their (control) inventors. If we consider that these inventors have, on average, applied for 3.4 patents in the five years previous to the departure and that the number of patents produced in the following five years by the control inventors is 3.72, a reduction of 2.21 patents corresponds to a decrease in productivity of more than 30 percent (=2.21/(3.40+3.72)).

Turning to inventors who remain with the acquired targets, Table 9 (top panel) indicates that their productivity also declines following the acquisition. Specifically, treated stayers produce approximately 0.92 fewer patents than their control counterparts after three years, with the gap widening to 0.97 patents after five years. Considering that these inventors had applied for an average of 4.04 patents in the five years preceding the acquisition, the observed reduction represents a drop in output of 11 percent - i.e. 0.97/ (4.04+4.20) -, demonstrating that acquisitions negatively impact the innovation activity of stayers, too.

Since consolidations are often justified by the goal of fostering synergies between the target and acquirer's research teams, the middle and bottom panels of Table 9 provide novel evidence on this process. Specifically, the table presents the post-acquisition patent output of stayers, distinguishing between two groups: those who do not collaborate with colleagues from the acquiring firm (middle panel) and those who do (bottom panel).

Some key insights emerge from the data. First, out of the 6946 patent observations, 57 percent (i.e., 3943) involve patent output produced in collaboration with inventors from the acquiring firm. This provides solid evidence of extensive joint research activities following the acquisition. Second, inventors who engage in collaboration are already more productive before the acquisition. Over the five years preceding the acquisition, they produced an average of 4.62 patents, compared to 3.26 patents for those who do not collaborate. As expected, this suggests that collaborations are not randomly established but are instead the outcome of a selection process, likely influenced by inventors' prior productivity and expertise. Third, the difference in post-acquisition patent output between the two groups is substantial. Non-collaborating inventors experience a significant decline in productivity, producing nearly two fewer patents over the subsequent five years. In contrast, those who collaborate see only a modest decline in output over the first three years, after which their productivity is not different from that of the control group. Since collaboration is an endogenous decision shaped by scientists' roles and expertise, further research is needed to better understand the role of collaboration in fostering synergies and sustaining innovation performance post-acquisition.

5.3. Robustness checks

This subsection presents additional robustness exercises addressing two main concerns. First, we examine whether our results are affected by potential selection into treatment based on firms' financial conditions.[34] Second, we assess whether a matching estimator yields results consistent with our main findings.

Controlling for Firms' Financial Conditions: To account for possible differences in financial characteristics between target and non-target firms, we merged our dataset with Orbis financial information for the period 1995–2015. This process required extensive name cleaning and multiple manual checks to ensure accurate matching.[35] We then included the logarithm of turnover, the logarithm of operating profit, and a dummy equal to zero when operating profit is negative (about 12 % of observations).

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[34] We also examined whether the estimation of inventor mobility could be affected by sample selection, since the probability of leaving is defined conditional on remaining active. To assess this, we estimated separate random-effects logit models for exit and mobility and computed the correlation between the inventor-level random effects across the two equations. The estimated correlation is small and negative (–0.08), indicating that unobserved factors influencing exit and mobility are only weakly related. This suggests that any potential selection bias in the mobility estimates is likely to be limited.

[35] The matching procedure substantially reduced the number of observations, as it was not always possible to accurately link our sample with the Orbis data due to missing information or inconsistencies in firm records. As a result, the final sample represents about 25% of the original observations.

Table 9

Change in Patent Output for Stayers.

This table shows the difference in number of patents between inventors who continue working for target firms and those of control group. The top panel presents data for all staying inventors, the middle panel refers to inventors who do not establish any collaboration with inventors from the acquiring company, and the bottom panel examines those who do establish a collaboration with the acquiring firm's scientists. Each "treated" inventor of a target firm is matched with two "control" inventors of non-target firms using the algorithm explained in Appendix B. Column (1) presents the mean cumulative number of patents over the five years before the treatment (i.e. acquisition). Due to perfect matching, the variable is the same for treated and control inventors. Columns (2) and (3) show the number of patents produced by treated and control inventors in the following 3 yr and 5 yr, respectively. Numbers in square brackets refer to 95 % confidence internal based on 1000 bootstrap replications for the difference in number of patents.

	#Obs	5 yr Cum Patents Before (1)	Cum Patents After 3 yr (2)	Cum Patents After 5 yr (3)
Stayer of Targets (Treated)	6946	4.04	2.13	3.23
Stayer of *Non*-Targets (Control)	13,892	4.04	3.05	4.20
			−0.92	−0.97
			[−1.03; −0.82]	[−1.13; −0.83]

	#Obs	5 yr Cum Patents Before (1)	Cum Patents After 3 yr (2)	Cum Patents After 5 yr (3)
ALL STAYERS				
Stayer of Targets (Treated)	6946	4.04	2.13	3.23
Stayer of *Non*-Targets (Control)	13,892	4.04	3.05	4.20
			−0.92	−0.97
			[−1.03; −0.82]	[−1.13; −0.83]
NO COLLABORATION				
Stayer of Targets (Treated)	3004	3.26	1.07	1.66
Stayer of *Non*-Targets (Control)	6008	3.26	2.72	3.73
			−1.65	−2.07
			[−1.78; −1.52]	[−2.25; −1.88]
WITH COLLOBORATION				
Stayer of Targets (Treated)	3943	4.62	2.94	4.43
Stayer of *Non*-Targets (Control)	7886	4.62	3.29	4.54
			−0.35	−0.11
			[−0.49; −0.20]	[−0.32; 0.10]

Table 10

Exit Rates – Checks of Robustness.

The table reports robustness checks for the baseline results on exit rates presented in Table 5. The two columns on the left reproduce the same coefficients shown in Table 5 to facilitate comparison. The two central columns show estimates obtained when including financial variables, namely the logarithm of turnover, the logarithm of operating profit, and a dummy variable equal to zero when operating profits are negative (which occurs in about 12 % of the observations). Finally, the last two columns present the results based on a matched sample, where treated inventors are matched to untreated scientists. The matching procedure includes also the financial variables used in the central columns.

Sample:	Table 5		Orbis - Finance		Matched	
Panel A: w = 5 v = 2						
Target	0.086***	0.076***	0.098***	0.078***	0.372***	0.266***
	(0.020)	(0.028)	(0.024)	(0.029)	(0.086)	(0.101)
Target[BIG]		0.016		0.032		0.187
		(0.038)		(0.044)		(0.126)
Financial Variable						
Operating Profit <0 (Dummy)			0.424*	0.422*		
			(0.239)	(0.239)		
ln(Operating Profit)			0.035**	0.035**		
			(0.017)	(0.017)		
#Obs	240704	240704	60743	60743	4899	4899
Panel B: w = 10 v = 5						
Target	0.139***	0.128***	0.151***	0.144***	0.170***	0.140***
	(0.014)	(0.021)	(0.026)	(0.026)	(0.035)	(0.032)
Target[BIG]		0.017		0.011		0.055
		(0.028)		(0.039)		(0.054)
Financial Variable						
Operating Profit <0 (Dummy)			0.778***	0.777***		
			(0.205)	(0.205)		
ln(Operating Profit)			0.062***	0.062***		
			(0.016)	(0.016)		
#Obs	166932	166932	42353	42353	10353	10353

The central columns of Tables 10 (exit) and 11 (separation) show that introducing these financial controls substantially reduces the sample size, but the estimated treatment effects remain stable. For exit, the coefficients on the dummy for negative operating profits are negative, suggesting that inventors employed by financially weaker firms are more likely to exit. By contrast, the coefficients on the logarithm of operating profits are positive and statistically significant, indicating that exit rates also increase for inventors in highly profitable firms. These results possibly reflect non-linearities linked to external job opportunities or internal restructuring following an acquisition. A similar pattern emerges when looking at separation rates: the coefficients on the financial variables show comparable signs and significance, and the effects of Target remain positive and close in magnitude to those in the baseline results.[36]

Matching as an Alternative Estimator. As a further robustness check, we implemented a matching approach as an alternative to our regression-based analysis. While matching and regression are not fundamentally distinct (both rely on the conditional independence of treatment assignment), regression offers greater flexibility in our context as it allows us to assess the role of individual covariates, distinguish between large and small deals, and examine heterogeneous effects depending on inventors' productivity within a simple and unified framework.

The rightmost columns of Tables 10 and 11 report the results obtained when we re-estimate the models using matched samples, as described in Appendix B, but also including the same financial variables used in the central column specifications. The results confirm the robustness of our findings. For exit, the matching procedure results in a substantial reduction in sample size to 4899 and 10,353 observations in Panels A and B, respectively, yet the coefficients on Target remain positive and statistically significant. For separation, the sample shrinks to 12,789 observations, but the estimated effects are again of similar magnitude to those in the baseline results.

Taken together, these robustness checks demonstrate that our findings are not sensitive to the inclusion of financial controls or to the estimation method. The relationship between acquisitions with exit rates and separation rates remain consistently positive and significant across specifications, reinforcing the credibility of our findings.

5.4. Inventor-level and firm-level results

Firm-level studies have shown that the largest deals in the pharmaceutical sector are linked to a decrease in patent output of consolidated companies, ranging between 20 and 30 percentage points. While, at first glance, this may seem concerning for innovation, the implications for societal welfare, including the scientists working in these companies' labs, are not clear. For instance, what if this decrease is coupled with a more than equal increase in knowledge produced by competitors, spurred by the arrival of scientists previously employed by the target? Our results provide credible evidence against this optimistic view.

First, acquisitions do not appear to be a "survival of the fittest" mechanism where only the most successful and productive inventors retain their jobs. In fact, we find that the probability of exit and departure drastically increases for all inventors, including those who were highly productive until the year of the acquisition. When combining the increase in exit and separation rates, we find values around 20 to 30 percent, which are in line with the decreases observed in firm-level studies. In other words, our inventor-level results indicate that exit and separation have similar importance in explaining the observed decrease in patenting of consolidated companies. Second, the substantial increase in the probability of exit suggests that the decrease in patents of consolidated companies cannot be offset by inventors migrating to other companies. These inventors are exiting the innovation market entirely, resulting in a permanent loss of human capital and new discoveries that will never come to fruition.

Third, even for inventors who move to new companies around the time of acquisitions, we find a substantial decrease in productivity. This decline in the productivity of leavers aligns with findings in the macro literature on the long-term effects of human capital reallocation. For instance, a recent study by Lachowska et al. (2020) on the causes of long-term earnings losses for displaced workers finds that the dissolution of valuable specific worker-employer matches can explain more than half of the wage losses. Lastly, the fact that inventors who remain at the target company (albeit under new ownership) also experience a decline in patent output compared to inventors with similar pre-merger trajectories, suggests that, despite the best intentions, acquisitions may fail to unleash synergies and instead disrupt existing innovative processes.

6. Conclusion

This paper studies *exit rates* and *separation rates* of inventors working for pharmaceutical firms that are targets of acquisitions. Our analysis finds an increase of exit rates between 7.6 and 17.5 percentage points and of departure rate between 12.2 and 18.9 percentage points around the period of an acquisition. Whereas one might reasonably anticipate that inventors who have historically produced fewer patents would be more likely to be laid off, potentially paving the way for an improvement in research productivity (patent per unit of R&D investment), we find a significant increase in the exit rates and separation rates across scientists also for highly productive scientists. Furthermore, the mere fact that an inventor is classified as a leaver means that she produces new patentable knowledge after moving to a new firm: inventions that the merged companies could have secured for themselves. This suggests that the dynamics we document are not solely the result of a deliberate decision to terminate the employment contracts of less productive scientists (*optimal scientist selection*) but may also be the unintended consequence of unforeseen integrational challenges, leading to the departure of key scientists (*negative selection*).

In terms of patent output, we find that exit is associated with a decrease of around two patents per inventor, corresponding to a

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[36] We also tested alternative ratios, such as operating margin (EBIT/Revenue) and asset turnover (Revenue/Assets), which produced qualitatively similar though less precisely estimated results.

Table 11

Separation Rates – Checks of Robustness.

The table reports robustness checks for the results on separation rates presented in Table 6. The two columns on the left reproduce the same co-efficients shown in Table 6 to facilitate comparison. The two central columns show estimates obtained when including financial variables, namely the logarithm of turnover, the logarithm of operating profit, and a dummy variable equal to zero when operating profits are negative (which occurs in about 12 % of the observations). Finally, the last two columns present the results based on a matched sample, where treated inventors are matched to untreated scientists. The matching procedure includes also the financial variables used in the central columns.

Sample:	Table 6		Orbis - Finance		Matched	
Target	0.122***	0.141***	0.126***	0.170***	0.136***	0.187***
	(0.006)	(0.010)	(0.009)	(0.017)	(0.018)	(0.033)
Target^{BIG}		−0.034***		−0.069***		−0.068**
		(0.012)		(0.020)		(0.034)
Financial Variable						
Operating Profit <0 (Dummy)			0.042***	0.043***		
			(0.015)	(0.015)		
ln(Operating Profit)			0.002**	0.003**		
			(0.001)	(0.001)		
#Obs	760047	760047	210038	210038	12789	12789

reduction of over 30 percent in the expected output these scientists could have produced over their careers. We also find that, within three to five years after the acquisition, inventors who move to a new company produce, on average, two fewer patents than their matched controls, while those who remain with the acquiring firm produce one fewer patent. This reduction corresponds to a 30 percent decrease in patent output for leavers and 11 percent decline for stayers. Finally, inventors who remain with the acquired firms also experience a decline in output, producing nearly one fewer patent. We find that the most productive stayers up to the year of the acquisition are more likely to begin collaborating with colleagues from the acquiring firm. However, even this "selected" group performs slightly worse than the control group. Our results suggest that M&As may not unlock knowledge synergies in R&D among the research team of acquirers and targets, a rationale frequently cited by top executives of pharmaceutical companies to justify such transactions. On the contrary, consolidations are associated with a large decline in patent output, leading to a substantial loss in social welfare, as these patents, had they been produced, could have provided the knowledge base to create more cost-effective medical treatments. Our results complement the findings by Cunningham et al. (2021), which show that pharmaceutical firms frequently engage in acquisitions with the primary aim to discontinue the target's innovation projects and pre-empt future competition.

Although our analyses focus on the pharmaceutical industry, the findings by Ng and Stuart (2022) and Arnold et al. (2023) suggest that our insights might extend beyond this specific market. The depletion of human capital associated with M&As can then represent a pervasive hindrance for technical advancement and productivity growth across various sectors. This concern is also supported by the findings in the macro literature that, following a mass layoff, workers who have been displaced experience a reduction in their "firm-specific" human capital, leading to decreased productivity in their subsequent jobs.

We emphasize again that the dynamics we document may stem from the firms' strategic decision to curtail investments in R&D because of changes in competitive pressure (dynamics studied in the industrial organization literature) as well as from the unexpected erosion in research capabilities due to integrational challenges and cultural conflicts (phenomena extensively explored in the management literature). Regardless of the underlying causes, our analysis gives strong support to the renewed effort shown by antitrust authorities to closely scrutinize the impact of acquisitions on innovation. In January 2022, the Justice Department's Antitrust Division and the FTC launched a joint public inquiry aimed at strengthening enforcement against mergers. As part of this initiative, the FTC raised questions about whether cost savings achieved through layoffs or capacity reductions should be considered cognizable efficiencies in merger guidelines. This perspective aligns with a growing body of literature advocating for close scrutiny of the anti-competitive effects of mergers in the labour market as part of merger control enforcement—see, e.g., Marinescu and Hovenkamp (2018). Our findings suggest that, in the case of consolidations in R&D intensive industries, the protection of workers goes hand-in-hand with consumer protection, because the (intended or unintended) exit and departure of scientists along with the unexpected challenges of integration, often undermine the ability of consolidated companies to improve innovative efficiency and, consequently, to introduce new and better treatments.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT4o in order to check for spelling errors and improve readability of certain parts of the paper. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Supplementary materials

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Data availability

Data will be made available on request

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