University of Southampton

Economics Department
University of Southampton
Southampton SO17 1BJ, UK

Discussion Papers in
Economics and Econometrics

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Carmine Ornaghi
(University of Southampton)

Lorenzo Cassi
(University of Paris)

No. 2306

This paper is available on our website
http://www.southampton.ac.uk/socsci/economics/research/papers

ISSN 0966-4246

Acquisitions, Inventors' Turnover, and Innovation: Evidence from the Pharmaceutical Industry*

Carmine Ornaghi† Lorenzo Cassi‡

December 2023

Abstract

There is robust evidence that M&As in the pharmaceutical sector have a negative impact on firms' patent output. In this paper we use data from the European Patent Office to investigate whether this decrease in patenting observed at firm level is associated with a halt in inventors' activity - i.e. human capital loss due to inventors' exit- or rather a migration of inventors of target firms to other research labs - i.e. human capital reallocation due to inventors' departure. We estimate that acquisitions are associated with an increase in exit rates of targets' inventors between 6 and 15 percentage points and of their departure rates ranging from 12 to18 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, 3.5 patents are foregone: a loss of 35 percent 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. Our finding suggests that concentrations are associated with a substantial loss in both worker and consumer welfare.

Keywords: M&As; inventors; innovation; patents; human capital loss; exit rates; separation rates; worker welfare.

JEL codes: G34; L41; J63; O31; O32.

* This article benefited from comments received at the 2023 Druid Conference, and seminars at the Competition and Market Authority in London (2022), Paris School of Economics (2022), and University of Southampton (2022). We are especially indebted to Tomaso Duso, Justus Haucap, Franco Mariuzzo, Tommaso Valletti, and Diego Zunino for discussions and for broadening our engagement with the literature. Research assistance from Matias Ortiz is gratefully acknowledged. This work was supported by the Economic and Social Research Council, UKRI - Grant ES/S015566/1.

† University of Southampton. Email: c.ornaghi@soton.ac.uk

‡ CES-Centre Economie de la Sorbonne, University of Paris 1 Panthéon-Sorbonne. Email: lorenzo.cassi@univ-paris1.fr

1. Introduction

Innovation is a key driver of firms' productivity increase, 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, a key driver of medical advancements and well-being, empirical studies have consistently found a significant decline in the number of patents after a consolidation – see Ornaghi (2009a) and Haucap *et al.* (2019).[3] Two different, though interrelated, dynamics within research labs can account for these firm-level trends. First, the post-merger optimisation and rationalisation of R&D activities often lead to the pruning of research projects and, in turn, the layoffs of R&D personnel.[4] Second, cultural differences and other integration challenges may prevent much-anticipated knowledge synergies from arising and instead lead to an unexpected decrease and, even, halt in the production of new knowledge for some of the researchers who keep on working for the consolidated firms, as well as to the unexpected departure of some key scientists.

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

[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] In a related study on the pharmaceutical company, Ornaghi (2009b) finds that human capital depreciation may be higher when there is a large overlapping between the technologies of merging companies.

[4] 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).

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.[5]

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 assess whether inventors of target companies are more likely to stop patenting (*exit rate*) and, if so, the number of patents they could have produced. Similarly, we estimate whether inventors of target firms have a higher probability of moving to another company (*separation rate*)[6] and whether such move is associated with an increase or deterioration in their productivity.[7]

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*). 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.[8] 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 6 to 15 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), and productivity (total number of patents 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.

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

[5] 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.

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

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

[8] Similar to other studies, we do not investigate exit and separation inventors of acquirers because large pharmaceutical companies 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.

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.

Next, we proceed to quantify the number of lost patents due to the increased exit rate and separation rate by matching inventors of target companies to inventors not involved in merger, but with identical productivity and career history up to the date of the merger. Even if inventors of target firms who are observed to exit or leave 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, one important advantage of using inventors' data compared to firm-level studies is that, for each *treated* inventor (i.e., an inventor that exits or leaves), we can choose a *control* scientist from a pool of thousands of individuals. Our findings suggest that exit leads to a loss of around 2.5 - 3.5 patents per scientist, equivalent to more than 35 percent of the expected output these scientists could have generated throughout their careers. And we find that scientists moving to other companies also suffer a significant decrease in productivity of around 30 percent in the following three years after the move.

In essence, 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. These findings can contribute to two important debates in competition policy, which have so far developed on parallel tracks: one regarding the impact of M&As on innovation,[9] and the other on the effect of consolidations on worker welfare.[10] This is surprising given that technological progress and human capital are often two sides of the same coin, as innovation is hardly manna from heaven but rather the result of human industry. Specifically, the large exit and separation rates we find seem to clash with 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

[9] An example of the growing interest amongst competition authorities is the Multilateral Working Group on pharmaceutical mergers, launched in March 2021 by the US FTC, the European Commission and other enforcement agencies. See www.ftc.gov/ftc-announces-multilateral-working-group.

[10] 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).

often invoked by firms to justify such deals. At the same time, it is difficult to see how the closure of R&D facilities and the consequent loss of human capital can generate *cognisable efficiencies* that can benefit patients and customers in the long run. Our findings serve as a strong warning for competition authorities that M&As in R&D intensive industries, such as pharma, might be detrimental to the welfare of workers and customers alike.

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 el 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.[11] 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; 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 a decrease in the productivity of research labs, i.e. a contraction in knowledge output (patents) above the reduction in investment. 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 portfolio, notwithstanding the following two differences, among others. First, our analysis concerns the research phase - the R in the R&D - whereas their study focuses on the development of new treatments (see Section 2 for details). 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

[11] See also Grabowski and Kyle (2010) for a review of the determinants and effects of M&As in the pharmaceutical industry

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 management literature on the relationship between M&As and labour turnover. 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 across various sectors of the Germany economy between 1997 and 2014, Gehrke et al. (2021) also find a 7.6% increase in the turnover rate for workers in consolidated companies.[14] In a study on the impact of acquisitions on turnover of inventors working for biotechnology firms, Verginer et al. (2022) find that in the four years after the acquisition, inventors in target companies are 20% more likely to move to another company compared to a control group of inventors not affected by acquisitions.

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 on mergers and innovation in one or more of the following aspects. First, this study provides a more comprehensive analysis by: (*i*) examining

[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.*"

simultaneously exit rates and separation rates, (*ii*) investigating whether these dynamics vary across scientists of different stature, and (*iii*) providing novel evidence on the number of lost patents that are associated with any increase in inventors' turnover and separation. 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, and our newly constructed dataset includes hundreds of thousands of inventors with at least one patent classified in the pharmaceutical space. Third, the use of inventor-level data allows us to identify the post-merger changes in patenting dynamics in a more rigorous way because individuals, differently from firms, do not physically merge into a new entity. Furthermore, whereas in firm-level studies the donor pool to construct the control group includes only a few hundred companies at best, our dataset includes thousands of inventors that work for firms not object of an acquisitions. This 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.

2. R&D and Patenting in Pharma

In this section, we describe the idiosyncrasy of innovation activities in the pharmaceutical industry, which is helpful to understand how patent data are used to address our research questions. 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.[16]

[16] 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)

A compound that successfully completes the pre-clinical tests (on average, one among 5,000-10,000 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 more than 7,000 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. Even after the expiration of a patent protecting an active compound, a drug may still be protected by other secondary patents with later expiration dates than the original patent, thus extending the scope and length of the protection of a product.

The mRNA technology used for Covid-19 vaccines provides an interesting example of the richness of the information that can be obtained from patent records. Two key discoveries paved the way for the development of mRNA vaccine technology in the first decade of the century. The first was the '*the incorporation of modified nucleoside into mRNA to increase stability and to ablate the mammalian innate immune response through the activation of Toll-like receptors*', a patented technology owned by the Trustees of the University of Pennsylvania.[17] The second was the '*the use of lipid particles to protect and deliver the RNA molecule into the cells*', a technology patented by *Protiva Therapeutics*, now *Arbutus Biopharma*. The combination of these two innovations led to a considerable expansion of the field, with an approximately 9-fold increase in patent publications between 2009 and 2020. The webpage of Moderna,

[17] Two scientists of the University of Pennsylvania, Katalin Kariko' and Drew Weissman, have been awarded the 2023 Nobel Prize in Medicine "*for their discoveries concerning nucleoside base modifications that enabled the development of effective mRNA vaccines against COVID-*.

one of the leading laboratories in mRNA technology, states that "*To date, Moderna has been granted more than 240 patents in the United States, Europe, Japan and other jurisdictions, protecting fundamental inventions in the mRNA therapeutics space, with several hundred additional pending patent applications covering key advances in the field*'.

The above examples illustrate how, even though most of the patents awarded to pharmaceutical companies deal with compounds that never reach the market, patents are a reliable measure of *R-stage* activities. Furthermore, the use of patent data allows us to measure not only scientists' productivity but also their mobility across different employers, with the shortcoming that their affiliations are observed only when they apply for a patent, similarly to how academics' affiliations can be inferred when they publish a paper in a journal. We explain this and other aspects of the data in the following section.

3. Data and Variable

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 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

[18] Version PatStat 2017, March.
[19] Downloaded in April 2016.
[20] Arora et al. (2021) has accomplished a similar task of dynamic reassignment of patent relative to the NBER patent data.

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 Zionidis, 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, 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.

[21] Based on Schmoch's classification of 35 technological fields (2008), 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.

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 provides information including the name of all applicants and whether this has changed over time. Second, we use the priority patents for all European patents that are an extension of patents previously submitted to another office (e.g. the US Patent Office), and use the applicant reported in these priority patents. 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.

To deal with the *affiliation issue*, we carefully define specific assignation rules based on an analysis of inventors' careers. By way of example, assume that a patent has three inventors and two applicants, *A* and *B*. If one of these three inventors applied in the past for a patent with applicant *A*, we choose *A* (and not *B*) as the applicant for this new patent. In general, we use 'conservative' rules to minimise the number of changes of employer in the inventors' career. Patents with more than one applicant account for around 10% of all patents.

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.

At the end of this process, our analytical dataset includes the 313,445 inventors with patents in at least two different years,[23] resulting in a total of 902,610 inventor x year observations over the period 1988 – 2015, equivalent to 2,88 observations for inventor 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 includes 513 deals among firms active in the pharmaceutical sector. To account for the diversity in acquisition values, we introduce a dummy variable, 'Big,'

[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.

indicating whether the acquisition's value exceeds 5 billion euros at the time of the acquisition. This criterion is met for 63 deals, corresponding to 12 percent of all acquisitions in our sample.

[Insert Table 1 Here.]

Figure 1 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.

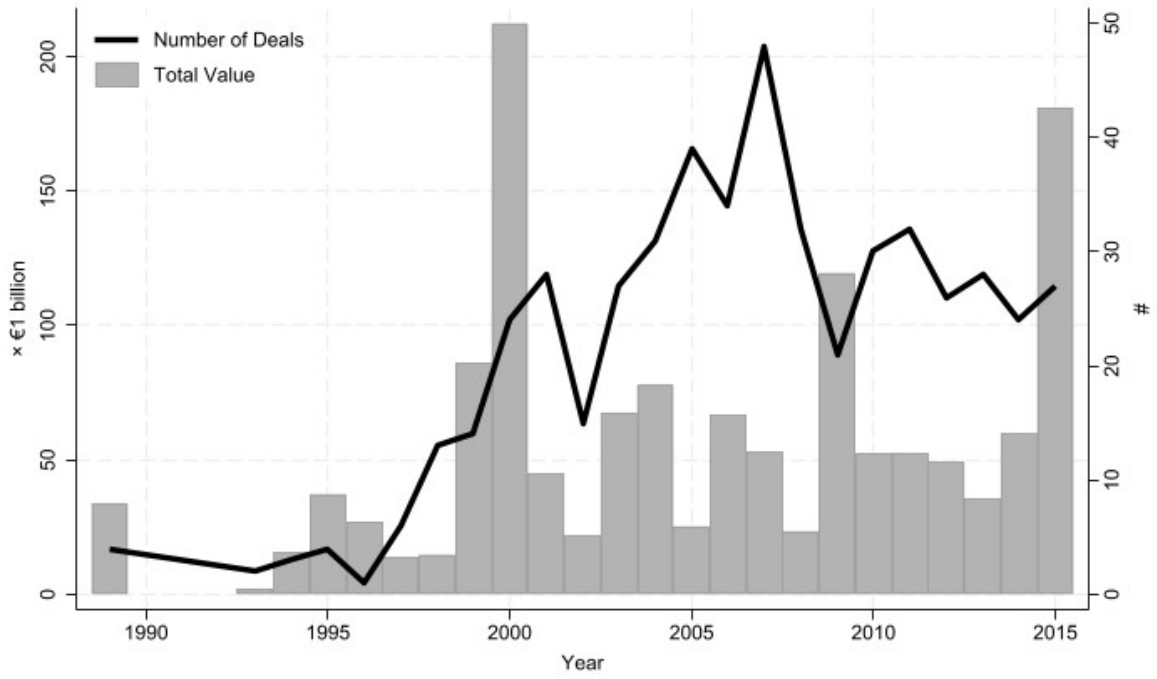

Figure 1. *Mergers and Acquisitions*

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, Figure 2 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.

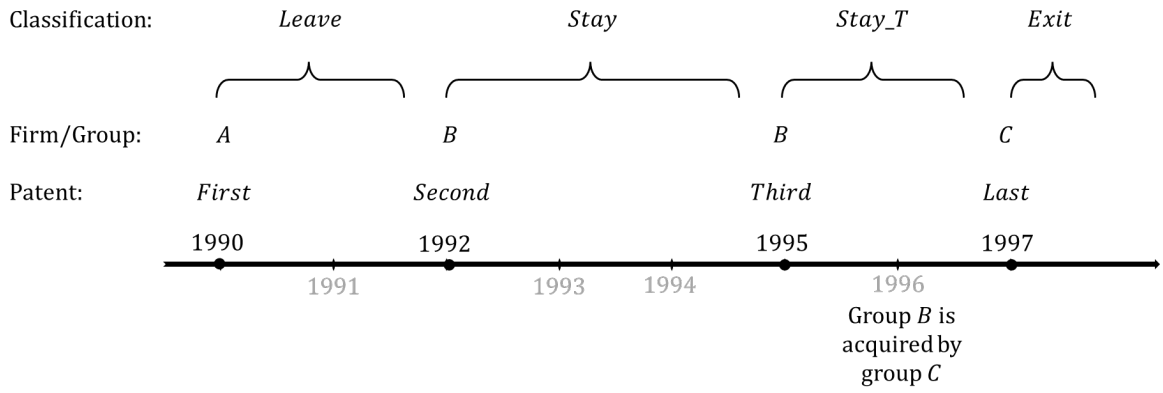

Figure 2. *Patents and Inventors Status*

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.

As said, our analytical sample consists of 902,610 observations from 313,445 inventors with patents in

at least two different years. The following table reports how these observations are distributed over the three possible status - *Stay*, *Leave*, and *Exit* – as well as the number of cases where the status *Stay* and *Leave* are observed after an acquisition (i.e., *Stay_T* and *Leave_T*). Explanation on how we construct the equivalent status *Exit_T* is deferred to Section 4.1.

[Insert Table 2 Here.]

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 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, which can control for the inventors' specialization in specific technologies.[24] 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).

Table 3 presents basic descriptive statistics for the variables described above.

[Insert Table 3 Here.]

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

[24] 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.

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 as *exiter* 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. First, 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. $t = \{t^f, \dots, t^\ell\}$. Some inventors are also observed in other periods between these two, which we denote with t^x. Furthermore, for any inventor we know the name of the group she works for in year t, which we denote by $c(t)$. Finally, we have information on whether and when a firm is acquired. The "whether" is represented by a dummy variable $T(c(t))$, which takes a value of 1 if firm c is a target at or after t, and the "when" is denoted by the time variable $t^T(c(t))$.

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 Figure 3, 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, 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 *alive* ($E^w = 0$), meanwhile, because she has a patent after w years since her first patent. Formally, we define the status *Exit* as follows:

$$E^w = \begin{cases} 1 & \text{if} \quad t^\ell \leq t^f + w \\ 0 & \text{otherwise.} \end{cases}$$

The treatment T refers to the fact that an inventor works for a pharmaceutical firm that is the object of an acquisition. We construct this variable as follows. First, we take the set of inventors with $E^w = 1$ and verifying whether their companies have been the target of an acquisition in a time window v after their last patent:

$$T^{v}_{(E^{w}=1)} = \begin{cases} 1 & \text{if} \quad T\left(c\left(t^{\ell}\right)\right) = 1 \ \wedge \ t^{\ell} \leq t^{T}\left(c\left(t^{\ell}\right)\right) \leq t^{\ell} + v \\ 0 & \text{otherwise} \end{cases}.$$

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 $v = \{2, 5\}$.[25].

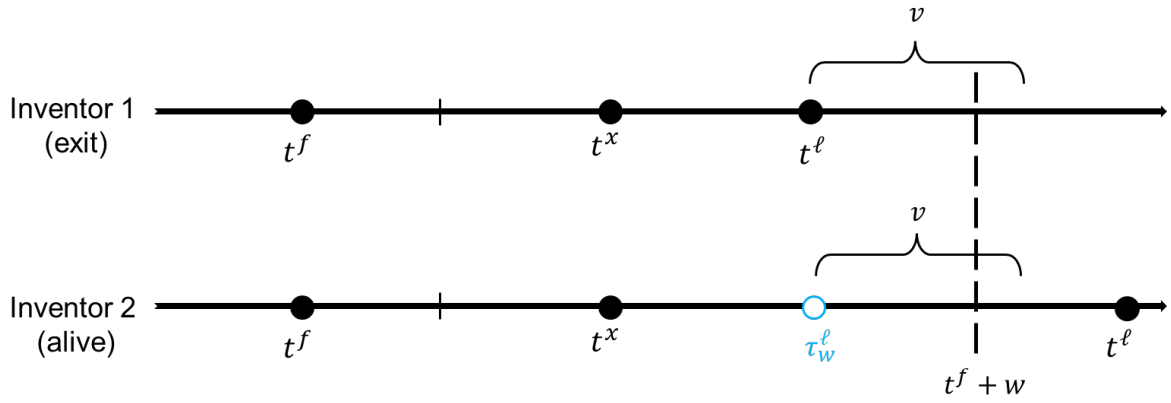

Figure 3. *Timeline of Patent Activity: Exit and Alive*

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} for *exiters* or the year of the last "imputed" patent, t^{ℓ}_w 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 $(t^f + w - t^x)$.

Note that the definition of the treatment variable generated for *exiters* 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

[25] 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 $2009 \leq 2000 + 10$, 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.

'hypothetical' last year, τ_w^{ℓ}, randomly drawn from a distribution equivalent to the observed distribution of t^{ℓ} for *exiters*. 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 Figure 3 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}, i.e. $c(t^x)$, has been the object of an acquisition. Formally:

$$T^{v}_{(E^w=0)} = \begin{cases} 1 & \text{if} \quad T\big(c(t^x)\big) = 1 \ \wedge \ \tau_w^{\ell} \leq t^T\big(c(t^x)\big) \leq \tau_w^{\ell} + v \\ 0 & \text{otherwise} \end{cases}.$$

After constructing the dependent variable, E^w, and the treatment dummy, T^v, we define the following empirical model for any inventor i working for company c:

$$Pr\big(E^w_{i,c} = 1 \big| \ T^v_c, \ \boldsymbol{X}_{i,c}\big) = G\big(\beta T^v_c + \Gamma \boldsymbol{X}_{i,c} + \delta_c\big), \qquad (1)$$

where $\boldsymbol{X_{i,c}}$ 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)[26] 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.

Equation (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

[26] 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 *exiter* or *alive* are evaluated exactly w years after the first patent, which implies that all inventors have the same experience.

dummy T^{BIG} taking value 1 for deals above €5 billion,[27] 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 as *exiters* is based patent data up to 2015, it is possible that some inventors, particularly those obtaining their first patent towards the end of the sample period, might be inaccurately classified as exiters 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 as an exiter 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 could be considered 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 exiters.

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:

$$P\left(L_{i,c,t} = 1 | \, T_c, \, \boldsymbol{X}_{i,c,t}\right) = \beta T_c + \Gamma \boldsymbol{X}_{i,c,t} + \delta_i + \delta_t + u_{i,c,t} \qquad (2)$$

[27] 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.

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 Figure 2. Accordingly, whereas equation (1) is estimated using only one observation per inventor, equation (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).[28] 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),[29] 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, Figure 4 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, i.e., $c(t^{x_1}) = A$, and that in period t^{x_2} she works for company B. Additionally, we know that company A was acquired at time $t^T(A)$ by another firm C. However, we cannot observe whether the inventor leaves firm A between $[t^{x_1}, t^T(A)]$ or between $(t^T(A), t^{x_2}]$. 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

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

[29] Of course, the cohort dummies are included only when inventor fixed effects are not included in equation (2).

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 equation (2) cannot be 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 ($T = 0$).

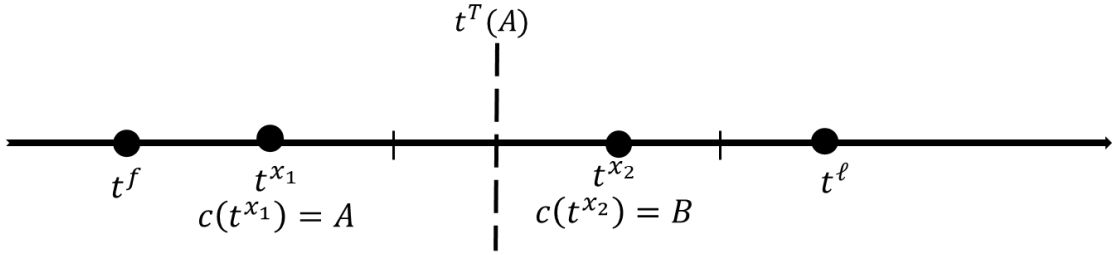

Figure 4. *Timeline of Patent Activity Inventors' Affiliation*

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.

4.3. Exit, Separation and Patent Output

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 separation rate. Specifically, for leavers of target firms, we estimate the change in patent output by comparing their number of patents after they move to a new lab to the patents of a control group of scientists who do not move and whose firm is not the target of an acquisition. For *exiters*, who by definition do not produce any patent in the future, the productivity loss is estimated instead by simply counting the number of patents of a control group of alive 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. 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). The same matching procedure is used to study change in patent output for the case of departure, with the only difference that the exact matching is not done on inactivity but on experience (see Footnote 26). A detailed explanation of the construction of the control group is provided in the Appendix.

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* more than once.[30] The matching procedure above is applied each time an inventor is classified as *Leave_T* but results are robust to dropping these serial *Leave_T* 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 ask inventors working on projects that (they think) are less promising to leave the company or to move to a different non-research role within the same organisation. If this is the case, our results may overestimate the loss (respectively, change) in productivity due to exit (respectively, separation). 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. The fact that top inventors are equally likely to exit as other inventors suggests that our treated group is unlikely to include exactly the scientists that would have not produced any patent in the absence of the merger.

5. **Results**

This section presents first the estimated exit rate and separation rate for inventors that work for target firms and then evaluate the associated lost or change in patent output.

[30] Thirteen inventors are assigned the status *Leave_T* twice and one inventor for three times.

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. $v=2$). Results for alternative values of w and v, namely $w=\{5,10\}$ and $v=\{2,5\}$, are similar as shown in Table 5 below.

We start by noting that the outcomes obtained using Probit and the 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 6 and 11.5 percent higher compared to other scientists whose employers are not the object of acquisitions.[31] 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 quartile for number of cumulative patents over the last five years are 24.7 percent less likely not to be 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 20.7 percent (i.e. 6.5 + 14.2) around the period of an acquisition. Finally, columns (5) and (6) show that similar results are obtained when we identify the set of more productive inventors using the number of patents over the last five years adjusted by number of citations.

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.

[31] We note that our estimates represent a conservative lower bound relative to those reported in other studies. 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. Verginer et al. (2022) do not explicitly investigate the impact of acquisitions on exit rates, but the first stage selection equation of the Heckman model indicate a decrease of 12%-15% in the probability of being active, although their estimates are not statistically significant.

[Insert Table 4 Here.]

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 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 15 percent, which is closer to the findings of other studies (see footnote 31).

The results for the interaction term *Productivity* x *Target* confirm that highly productive inventors, who are normally 15 to 25 percent less likely to stop patenting, experience an increase in the likelihood of exit that reduces their initial lower base-rate probability by around half.

[Insert Table 5 Here.]

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 18 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. (2022), who find a 20% higher probability of departure for inventors of targets. This similarity is particularly noteworthy considering the difference in estimation techniques and number of observations (760 thousand in our study *vs* under 5 thousand in theirs).

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).

[Insert Table 6 Here.]

In the rest of this section, we provide inventor-level estimates of (i) the number of patents lost for inventors with status *Exit_T* and (ii) the change in patent output associated with *Leave_T*. To this aim, for each (treated) inventor with status *Exit_T* or *Leave_T*, we select (control) inventors using the matching algorithm detailed in the Appendix.

Starting with a definition of *exit* based on a time window of five years after the first patent (w=5), the results in Panel A of Table 7 indicate a loss, on average, of 2.5 patents (respectively, 3.5 patents) over a period of 3 years (respectively, 5 years) 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 38 percent - i.e., 2.43/(2.43+4.02) - to 48 percent - i.e., 3.46/(3.46+4.02) - of the expected output that these scientists could have generated over their careers The results in Panel B show that we find qualitative similar results if when we look at exit ten years after the first patent.

The following back-of-the-envelope calculations can provide a broad perspective on what this loss in patent output means at the aggregate level. Using the scenario with w=5 and v=2 as an illustration, our analytical dataset includes 240,704 inventors and 2,453 exits (see details in the Appendix). Assuming a 10% exit rate associated with acquisitions, we have an excess exit of 223 inventors (=2,453 – 2,230) of target firms. Each of these inventors could have generated 2.43 patents in the subsequent three years, resulting in an annual loss of 181 patents. Given an average production of 15,494 patents per year for the 240,704 inventors in our dataset, this results in a loss of 1.2 percent – i.e., 181 out of 15,494 patents. Similar calculations for the scenario with w=10 and v=5 indicate that the ratio of lost patents increases to 3.4 percent. As already noted, we cannot say whether the inventors that exit our dataset are still doing research in a lab or whether they have moved to other (non-research) jobs within the same organisation or in other firms. Accordingly, it is not possible to assert that aggregate welfare, including worker welfare, would be higher if these individuals continue working in the labs of the targets rather than the alternative careers they might have started pursuing. However, our calculation does highlight the potential substantial loss in consumer welfare associated with acquisitions under

the reasonable assumption that innovation in medical treatments is among the most important activity to improve human well-being.

[Insert Table 7 Here.]

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 constructed by selecting inventors that do not move (see Appendix for details). 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 3.18 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 3.46, a reduction of 2 patents corresponds to a decrease in productivity of 30 percent (=2/(3.18+3/46)).

[Insert Table 8 Here.]

The inventor-level results presented above indicate that the increase in exit rates and separation rates play a significant role in explaining the large decrease in patenting that has been observed in firm-level studies of the pharmaceutical industry - see Ornaghi (2009a) and Haucap et al. (2019). Additionally, the decline in productivity of *leavers* align closely with the findings in the macro literature investigating 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 of displaced workers, find that the dissolution of valuable specific worker-employer matches can explain more than one-half of the wage losses.

6. **Conclusions**

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 6 and 15 percentage points and of departure rate between 12 and 18 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 the cost tag attached to exit consists of 2.5 and 3.5 patents lost for each inventor, which corresponds to a decrease of 35 percent of the expected output these scientists could have produced over their careers. We also find a reduction of 2 patents for inventors moving to new company compared to their control group, which corresponds to a 30 percent decrease in their productivity in the following three years after the move.

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 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. In her opening remarks on launching this public inquiry, FTC Chair Lina M. Khan raised the question: '*[W]hen a merger is expected to generate cost savings through layoffs or reduction of capacity, should the guidelines treat this elimination of jobs or capacity as cognizable "efficiencies"*?' A growing literature supports a negative answer to this question, advocating for close scrutiny of the anticompetitive effects of mergers in the labour market as part of merger control enforcement - see, e.g., Marinescu and Hovenkamp (2018) and Tong and Ornaghi (2021). Our findings suggest that a complete answer to this question involves taking dynamic efficiency into account as well: in the case of mergers in R&D intensive industries, the protection of workers can go hand-in-hand with consumer protection, because the (intended or unintended) depletion of human capital due to scientists' exit and departure could undermine the ability of consolidated companies to improve manufacturing processes and to introduce innovative products.

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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)	2,679,925	8,283,210	10,050	93,409,440
Target^{BIG} Value	63 (12,3)	17,161,133	17,749,976	5,200,000	93,409,440

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 also report the number of observations where the inventors work for a firm that is object of an acquisition. 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. When studying exit rates, we check robustness of results for alternative values of w and v.

		#Obs (%)	
Leave		11098 (12,3)	
	of which *Leave_T*		2679
Stay		651082 (72,1)	
	of which *Stay_T*		7105
Exit		140530 (15,6)	
Total		902610 (100)	

Table 3. Descriptive Statistics

This table provides descriptive statistics on the covariates that are used to estimate exit rates - equation (1) – and separation rates – equation (2). For time-invariant variables, the number of observations indicates the number of inventors. For time-variant variables, the number of observations refers to the number of inventors multiplied for the number of years we observe them.

Variable	#Obs	Mean	Std. Dev.	Min.	Max
Time Invariant (Inventor)					
Year first patent	313,445	2000.69	7.36	1976	2014
Year last patent	313,445	2006.09	6.36	1989	2015
Time Variant (Inventor X Year)					
Inactivity	902,610	1.27	1.64	0	32
Experience	902,610	4.46	4.55	1	37
Technologies dummys (#specialised IPC classes)	902,610	2.41	1.64	1	19
Productivity (simple patents)	902,610	0.19	0.39	0	1
Productivity (weighted patents)	902,610	0.22	0.4	0	1
Target	902,610	0.013	0.12	0	1
Target Big	902,610	0.008	0.089	0	1
Group patent	902,610	2030.33	3965.77	1	29115

Table 4. Exit Rates

This table presents the likelihood of exit of inventors estimated using a probit model or linear probability model (LPM). 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. See Figure 3 for an example of how *Exit* and *Target* are constructed. In this table, we use w=5 and v=2; robustness checks for different values of w and v are shown in Table 5. In columns (3) and (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. 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 more than 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	Probit	LPM	LPM	LPM	LPM
	(1)	(2)	(3)	(4)	(5)	(6)
Target	0.115***	0.098***	0.065***	0.059**	0.078***	0.068**
	(0.026)	(0.031)	(0.020)	(0.027)	(0.020)	(0.030)
$Target^{BIG}$		0.028		0.010		0.015
		(0.048)		(0.037)		(0.038)
Productivity			-0.247***	-0.247***	-0.193***	-0.193***
			(0.004)	(0.004)	(0.005)	(0.005)
Productivity x Target			0.142***	0.144***	0.092***	0.115***
			(0.026)	(0.034)	(0.023)	(0.035)
Productivity x $Target^{BIG}$				-0.004		-0.037
				(0.047)		(0.045)
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			0.265	0.265	0.256	0.256
#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*. See Figure 3 for an example on how *Exit* and *Target* are constructed. 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 quartile 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* (3)	LPM *w=5 v=2* (4)	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	0.065***	0.059**	0.155***	0.153***	0.064***	0.082***	0.125***	0.117***
	(0.020)	(0.027)	(0.017)	(0.022)	(0.013)	(0.020)	(0.014)	(0.020)
$Target^{BIG}$		0.010		0.004		-0.026		0.012
		(0.037)		(0.031)		(0.025)		(0.026)
Productivity	-0.247***	-0.247***	-0.246***	-0.246***	-0.151***	-0.151***	-0.152***	-0.152***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Productivity x Target	0.142***	0.144***	0.086***	0.082***	0.082***	0.063*	0.077***	0.079***
	(0.026)	(0.034)	(0.018)	(0.024)	(0.024)	(0.036)	(0.016)	(0.026)
Productivity x $Target^{BIG}$		-0.004		0.007		0.028		-0.002
		(0.047)		(0.034)		(0.046)		(0.033)
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	0.265	0.265	0.267	0.267	0.376	0.376	0.378	0.378
#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. See Figure 4 for an example of how *Leave* and *Target* are constructed. 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	0.157***	0.187***	0.122***	0.152***	0.125***	0.146***
	(0.014)	(0.025)	(0.006)	(0.008)	(0.006)	(0.010)
$Target^{BIG}$		-0.051		-0.034***		-0.035***
		(0.031)		(0.012)		(0.012)
Productivity	-0.019***	-0.019***	0.015***	0.015***	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Productivity x Target	-0.041**	-0.023	-0.021*	-0.003	-0.035***	-0.019
	(0.016)	(0.032)	(0.011)	(0.020)	(0.011)	(0.019)
Productivity x $Target^{BIG}$		-0.027		-0.029		-0.026
		(0.036)		(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	0.197	0.197	0.033	0.033	0.034	0.034
#Obs	760047	760047	760047	760047	760047	760047

Table 7. Exit Rates and Lost Patents

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. 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 3yr and 5yr 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=10 and v=5. Numbers in square brackets refer to 95% confidence internal based on 1,000 boostrap replications for the difference in number of patents.

	5yr 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)	4.02	0	0
Non-Exit (Control)	4.02	2.43	3.46
		-2.43	-3.46
		[-2.33 ; - 2.53]	[-3.31 ; -3.61]
Panel B : w=10 and v=5			
Exit (Treated)	3.18	0	0
Non-Exit (Control)	3.18	2.03	2.95
		-2.03	-2.95
		[-1.95 ; -2.10]	[-2.83 ; -3.06]

Table 8. Separation Rates and Change in Patent Output

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 the Appendix. 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 3yr and 5yr, respectively. Numbers in square brackets refer to 95% confidence internal based on 1,000 boostrap replications for the difference in number of patents.

	5yr Cum Patents Before (1)	Cum Patents After 3 yr (2)	Cum Patents After 5 yr (3)
Leaver (Treated)	3.18	0.73	1.46
Non- Leaver (Control)	3.18	2.15	3.46
		-1.78	-2.00
		[-1.90 ; -1.67]	[-2.17 ; -1.82]

Appendix

Construction of the Control Group to estimate Number of Lost Patent associated with Exit

Results in Table 4 and Table 5 show that inventors of target firms have a higher probability of exit. To estimate the number of patents inventors with status *Exit_T* (i.e. E=1 and T=1) might have produced if it were not for the acquisition, we select similar inventors that (i) are still alive (E=0) and (ii) do not work for firms that are the object of an acquisition (T=0).

As explained in Section 4, the classification of the exit status (E) and the treatment indicator (T) depends on the values of, respectively, w (number of years after the first patent) and v (time window after the last patent). Specifically, the size of the treated group increases with w and v, as an inventor is more likely to be classified as *Exit_T* for higher values of w and v. At the same time, the total number of observations decreases for higher values of w because we cannot construct the exit status for more recent cohorts of inventors - e.g., inventors with a first patent in 2008 cannot be included when w=10 because our patent data ends in 2015 and $2008+w>2015$ for w=10. Table A1 below shows that the number of treated individuals is 2,453 for values of w=5 and v=2 (left-hand side) and 5,889 for w=10 and v=5 (right-hand side), while the total number of observations decreases from 240,704 to 166,932.

Table A1: Treated and Potential Controls

	Target		
Exit	0	1	Total
0	99,205	969	100,174
1	138,077	2,453	140,530
Total	237,282	3,422	240,704

	Target		
Exit	0	1	Total
0	40,248	646	40,894
1	120,149	5,889	126,038
Total	160,397	6,535	166,932

The table above also shows that we can always rely on a large pool of donors with E=0 and T=0. For instance, we have an initial pool of more than ninety-nine thousand inventors for w=5 and v=2. From this starting pool of donors, we select, for each treated inventor, identical inventors (exact matching) on the following characteristics:

1) Year of first patent.
2) Number of cumulative patents over the last 5 years.
3) Years of inactivity, defined as number of years since the last patent (see Figure 3 an example).

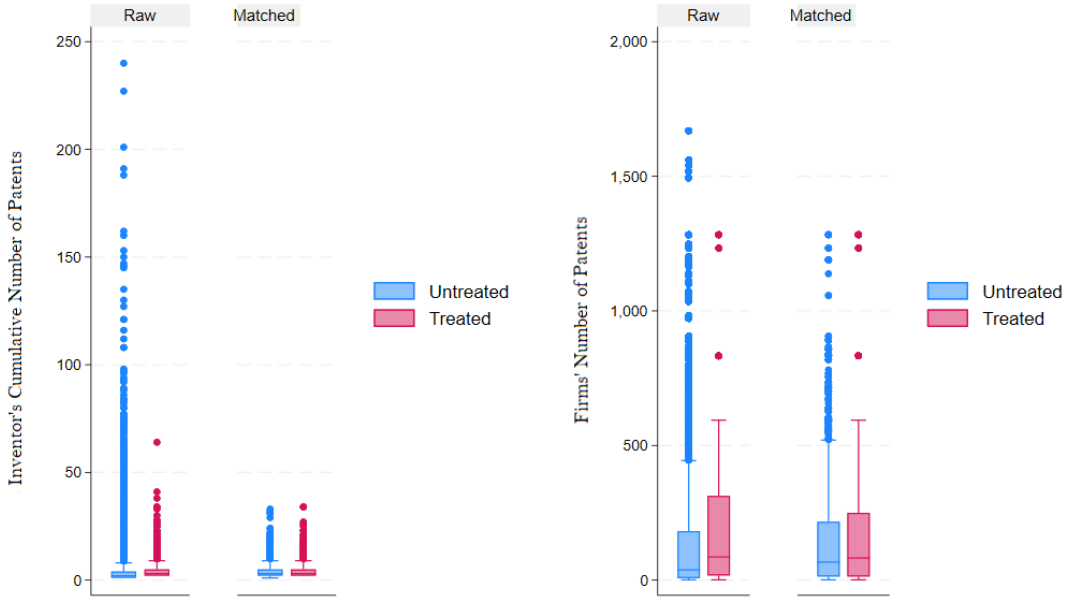
Condition (1) allows us to control for differences in the life-cycle and secular time effects, whereas condition (2) and (3) enable us to select inventors with identical patent productivity before the treatment.

Using the (still large) surviving pool of donors, we select, for each treated inventor, the two control inventors that are closest along the following two dimensions:

4) Number of cumulative patents since the first patent.
5) Number of patents of the firms.

Condition (4) allows us to control for any residual difference in productivity beyond the last five years, which is relevant when the exit/alive status of inventors is defined using w=10. Condition (5) addresses the fact that inventors' productivity can vary depending on the size of the firms they work for. As a perfect match between treated and control inventors on these two covariates would imply a drastic reduction in the sample, we use instead the nearest-neighbor matching based on the multivariate Mahalanobis distance. The figure below shows that the matching sensibly reduces the difference between treated and control groups for the two covariates compared to the initial raw data.

***Figure A1**: Difference in Patents between Treated and Control Groups before and after the Matching*



As a result of the steps above, each treated inventor is matched to two control inventors. Table 7 shows that the number of treated and control inventors is, respectively, 2418 and 4836 - i.e. 2 x 2428 – for *w=5* and *v=2* (Panel A) and 3128 and 6256 for *w=10* and *v=5* (Panel B). It is interesting to note that, despite using an exact matching on the covariates described above, we have a reasonably high number of treated inventors that are successfully matched to controls.

Construction of the Control Group to estimate the Change in Patent Output for Leavers

The algorithm used to match *leavers* of target firms to control inventors is similar to the one used for *exiters* described above. Treated inventors are now those classified as *Leave_T*, i.e. inventors that during the spell of time between two patents leave an employer (L=1) which is object of an acquisition (T=1). Note that, while the dataset used to investigate exit includes only one observation per inventor, for departure rates, inventors can have multiple observations as explained in Section 3.

We start with an initial number of 2,675 treated observations, which corresponds to 2,660 inventors as thirteen of them are assigned the status *Leave_T* twice and one for three times. The initial donor pool is made by more than 480 thousand observations, which refers to around 220 thousand inventors who have always worked for the same firm (L=0) and whose employers have not been the object of an acquisitions during their tenure (T=0). Additionally, we do not use the final observation of each inventor because, by definition, all inventors are classified as *exiters* at the time of their last observation. From this initial pool, we select, for each treated observation, an observation that refers to an inventorwith identical: (1) Years of First Patent; (2) Number of cumulative patents over the last 5 years; and (3) Years of experience, defined as number of years since the first patent. Note that the only difference with the matching algorithm used for *Exit* is that we use years of experience, instead of inactivity.

From this surviving pool of donors, we then proceed to select, the two inventors with the closest (4) Number of cumulative patents since the first patent and (5) Number of patents of the firms (nearest-neighbor matching based on the multivariate Mahalanobis distance). The figure below shows that, also in this case, the matching sensibly reduces the difference between treated and control groups for these two covariates compared to the initial raw data.

Figure A2: *Difference in Patents between Treated and Control Groups before and after the Matching*

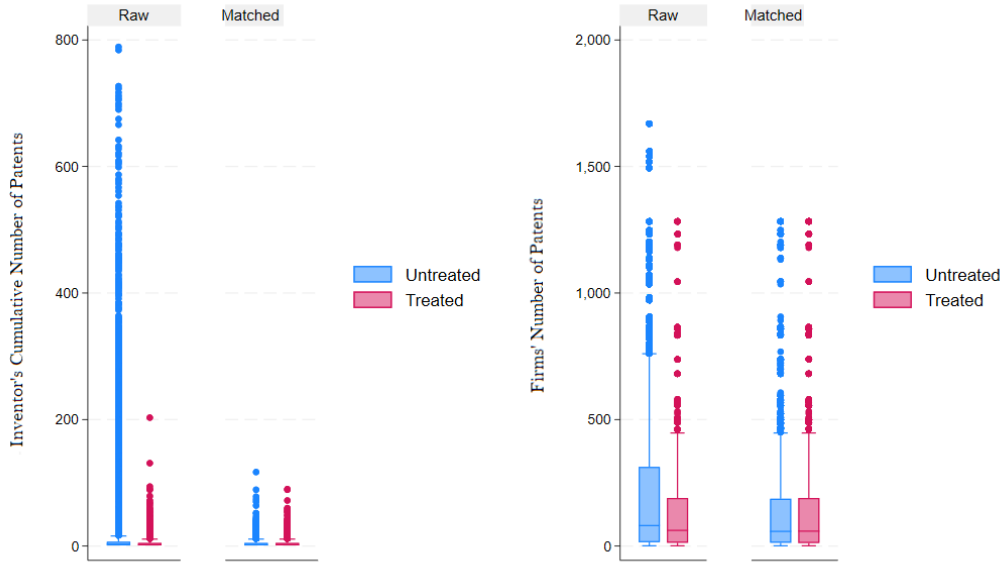


Table 8 shows that the number of treated and control observations is, respectively, 2650 and 5300 - i.e. 2 x 2630. This means that only twenty-five treated observations are lost when applying the matching algorithm.