The Impact of Acquisitions on Inventors' Turnover in the Biotechnology Industry

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Abstract. In high-tech industries, where intellectual property plays a crucial role, the acquisition of intangible assets and employees' tacit knowledge is an integral part of the motivation for Mergers and Acquisitions (M&As). Following the molecular biology revolution, the wave of takeovers in the biotechnology industry in the Nineties is a well-known example of M&As to absorb new knowledge. The retention of critical R&D employees embodying valuable knowledge and potential future innovation is uncertain after an acquisition. While not all employees might be relevant for the success of the takeover, inventors are among the most valuable. This is especially true for the acquisition of an innovative start-up. This paper estimates how likely an inventor working for an acquired biotechnology company will leave. We find that inventors affected by acquisitions are 20% more likely to leave the company by a difference-in-differences approach matching both firms and inventors.

Keywords: merger and acquisition; patent; inventor mobility; biotechnology industry; innovation

JEL Codes: G34; J61; J62; O32; O34

1 Introduction

A firm's post-acquisition performance depends on its ability to reorganise the activities to exploit the assets and capabilities of the acquired company (Fernandez De Arroyabe Arranz and Hussinger, 2018). Crucially for Research and Development (R&D) intensive industries, the success of the acquisition depends on both tangible and intangible assets. Therefore, intellectual property, both codified (e.g., patents) and tacit (i.e., crucial employee know-how), must be managed with care to avoid jeopardising the takeover. Gottweis and Prainsack (2006) find that employee turnover is a

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primary reason for Mergers and Acquisitions (M&A) failure, with reportedly up to three-quarters of these deals failing (King et al., 2004). This is particularly relevant in knowledge-intensive industries after a paradigmatic change, such as the life sciences, which saw a rush of M&As in the Nineties (Riccaboni and Pammolli, 2002) to absorb knowledge in the emerging field of biotechnology. M&A deals in 1999 involving US companies were worth well over 500 Billion USD (Danzon et al., 2007), highlighting the economic importance of the practice. At the time, the target companies were primarily new biotechnology firms (NBFs) founded since the mid-Seventies and poised to challenge the leadership of established pharmaceutical companies (Orsenigo et al., 2001; Riccaboni and Pammolli, 2002; Béraud et al., 2020; Pammolli et al., 2021). The biopharmaceutical sector is an exceptionally R&D intensive sector, with Pharmaceutical Researchers and Manufacturers of America (2012) claiming that as much as 17% of revenue is devoted to R&D, compared to the US industry average of 4% (Danzon et al., 2007). The importance of patents specifically, and intellectual property in general, is well-known in the bio-pharmaceutical industry (Cohen et al., 2000). Therefore the knowledge embodied in patent inventor teams is crucial to developing innovative drugs.

Inventors, the employees behind these innovations, play a crucial role in knowledge production; therefore, their retention after M&As is vital. The retention of the inventors is critical considering their tacit and "socially complex" knowledge (Barney, 1991), i.e. firm capabilities which emerge from complex social interactions. Additionally, the extant literature on M&A success indicates that technological complementarities are crucial for post-merger productivity (Kapoor and Lim, 2007; Ahuja and Katila, 2001; Cloodt et al., 2006). The reaction of inventors to M&As is therefore of critical importance.

An inventor working for an acquired company can respond in several ways to the acquisition. The most desirable outcome in our framework is that they (1) stay with the company and continue contributing to innovation and patent production. However, this is not the only alternative they have. The alternatives we focus on in this work are that they (2) continue their patenting activity but do so for a third party unrelated to the M&A or (3) transition to a different role where former inventors are no longer active in patent production.

Most of the extant literature addresses turnover and related performance issues related to top management (e.g. Hambrick and Cannella (1993); Haveman (1995); Haleblian et al. (2009)), general employee turnover (Carriquiry, 2018) and, to a lesser degree, the impact of M&As on R&D personnel (Ernst and Vitt, 2000). Fernandez De Arroyabe Arranz and Hussinger (2018) look at the turnover rate of inventors following an M&A event and finds that only 4% of them leave. The study focusing on which industry the leavers end up in finds several interesting mobility dynamics of inventors as they move across high, mid and low tech industries following the event. One of the main shortcomings of the extant literature on the relationship between the acquisitions of innovative firms and the turnover or R&D personnel is the possible presence of confounding effects that might increase the likelihood that a company will become a target for acquisition and the chance that inventors will leave. Therefore, it is difficult to establish a causal relationship between the event (i.e., the acquisition) and the investors' decision to leave the target company.

This study relies on matching at the inventor and firm-level combined with a difference-in-differences methodology to overcome this limitation. To better isolate the decision of the inventors to leave because of an acquisition took place, we focus on a specific phase of an innovation-intensive sector's industry life cycle immediately after the pharmaceutical industry's molecular biology revolution. We look specifically at acquisitions in the biotechnology industry for two reasons. First, it represents an R&D intensive sector and is hence relevant for our analysis on retention of skilled human capital and intellectual property. Second, in the Nineties, the pharmaceutical sector has experienced an increased rate of M&A events, ranging from mergers between large pharmaceutical companies to acquisitions of new biotechnology firms. In the same period, (Riccaboni and Pammolli, 2002) and Tomasello et al. (2017) find that research alliances in general and the biotechnology industry, in particular, were on the rise. This result shows that firms were eager to pool resources to be at the cutting edge of R&D and M&As are a natural next step in the pooling of resources. Moreover, focusing on the first wave of acquisition of biotech firms gives us the ability to look at the long-run effects of those events.

In our analysis, we address whether an acquisition harms inventor retention. Note that we *only* consider outright acquisitions and not any weaker form of M&A such as partial or complete mergers. The treated units of the analysis will be companies and inventors involved in acquisitions. We use acquisitions exclusively to sidestep several difficulties we might encounter when considering mergers. First, by only considering acquisitions, there is a clear indication of which entity will have control and that no new legal entity will emerge from the transaction.[1] Second, the relationship of acquired and acquiring allows us to identify the deal's target, which is arguably most likely to be affected by changes, i.e., the acquired firm.

We aim at estimating the turnover rate due to acquisitions, which we find to be 20%, in line with Ernst and Vitt (2000) and Ranft and Lord (2000). Therefore we contribute to the literature on the consequences of a firm's acquisition on R&D productivity by providing further evidence that M&As have a detrimental effect on the retention of the inventive labor force.

The remainder of this work is structured as follows. In Section 2 we discuss the extant literature on employee turnover and M&As. Section 3 introduces the various data sets we merge to perform our analysis. The empirical strategy is presented in Section 4, as well as the various steps involved in our matching procedure. Section 5 describes our

[1] In the actual analysis we make sure that after the acquisition the name of the acquired company does not change and if it does we try to identify it through variations of the acquired and acquiring company's names.

main results. Finally, we discuss the results, their importance, how they fit in the extant literature and the limitations of this study in Section 6.

2 Acquisitions and inventors' turnover

In this work, we take a knowledge base view of the firm[2] to argue that among the various motives for the takeover of innovative firms, in addition to the acquisition of codified intellectual property (i.e., patents), the retention of tacit knowledge held by employees is an essential factor in R&D intensive industries.

Consequently, retention of employees involved in R&D as witnessed by their patent applications is a desirable outcome. Hambrick and Cannella (1993) finds evidence that the departure of essential employees was a significant predictor of poor post-merger performance. The authoritative work by Coff (1997) on the management of human assets and their tacit knowledge reiterates this sentiment. It argues that retention of key employees is challenging to get right in acquisitions. Carriquiry (2018) note that the disruptive nature of an acquisition, a significant managerial intervention, may have an overall negative effect on the turnover rate.

Several studies focusing on M&As in the Nineties have found that top executives and management are more likely to leave the firm following an acquisition. Haveman (1995), evaluating the retention rate in M&As involving financial companies, finds that top executives are prone to leave the firm following the event. Ranft and Lord (2000) finds that according to a survey involving 89 firms which were part of M&As senior executives were the most likely to leave and 22.7% R&D personnel left on average. However, they also find that R&D personnel is considered to be the most crucial class of employees to retain. A result of this literature is that acquisitions affect retention rates.

Specifically, due to changes in routines and managerial hierarchies as well as uncertain career prospects (Hobman et al., 2004), an inventor may decide to leave a company. Similarly, Holtom et al. (2005) argue that shocks such as M&A "trigger" a reevaluation of career and life goals of the affected employee. For example, an employee wanting to leave all along takes the M&A as a sign to act, or similarly, differences in the managerial "culture" could trigger a reevaluation. It emerges clearly from the meta-analysis on the turnover by Griffeth et al. (2000) that the motivations for turnover are many and varied. Still, shocks and disruption to business-as-usual can lead to higher than average turnover. These observations and results lead us to formulate Hypothesis 1, which we will address in more detail in the Section 5

Hypothesis 1 (H1) *Following an acquisition, inventors are more likely to leave the acquired firm than a comparable (control) firm.*

[2]Following the definition of knowledge base view of the firm given by Grant (1996) a firm is considered to be a vehicle to organise tacit and complex social knowledge held by individuals to create products and services.

Common reasons proposed for why M&As take place, combine elements of vertical and horizontal integration, economies of scale and scope, and transfer of specific assets or capabilities (Danzon et al., 2007; Higgins and Rodriguez, 2006; Ravenscraft and Long, 2000). Higgins and Rodriguez (2006), analysing pharmaceutical firms in the Nineties, find that companies with expiring patents and declining internal productivity are more likely to engage in M&As. The rationale behind this proposed mechanism is that expiring patents free up production and R&D capacity. In contrast, fixed and sunk cost assets (i.e. employees and factories) can be used to enhance the impact of an acquired company that has a viable compound but lacks productive and marketing capabilities. Similarly, Villalonga and McGahan (2005), looking at 9 276 acquisitions between 1990 and 2000, find that the acquisition route, as opposed to alliances and divestitures, are chosen more often if the target has more valuable technological resources at its disposal.

Moreover, M&A may lead to positive stock performance as Higgins and Rodriguez (2006) find. M&As identified as being conducted with the expressed purpose of R&D consolidation, lead to abnormal returns to both the acquired and the acquiring company. However, this comes with the caveat that the acquired firms were found more likely to experience financial difficulties (Danzon et al., 2007). In particular, Ravenscraft and Long (2000) find that acquired firms tend to experience negative stock returns up to 18 months before the takeover.

We argued that the retention of inventors is essential and looked at possible reasons a given inventor might leave; however, the employment relationship will only continue if it is also in the best interest of the acquiring firm. Possible reasons for terminating inventors after acquisitions vary, starting with duplicating skills already covered by the acquiring firm or abandoning a research area altogether. This last point is in line with the finding by Zhu (2018) that acquiring firms tend to sell off acquired patents right after the event. However, it is still a valid assumption that the acquiring firm would not want to decimate its newly acquired inventors immediately, arguably valuable assets, but transition them out gradually. On the other hand, as argued above, inventors might see the shock as a nudge to change employer. Arguably, this can be more relevant for inventors with a substantial overlap with the acquiring firm since their knowledge might be more valuable on the market than in the merged company. Similarly, inventors whose field of expertise is not related to the core competencies of the acquiring firms might leave to join other companies where they have a better fit.

Concerning the duplication of expertise, technological similarity, and post-merger performance of firms, Kapoor and Lim (2007), Ahuja and Katila (2001), Cloodt et al. (2006) find that the patenting output and innovativeness is highest if the technological profiles of the acquiring and acquired firm overlap partially. Following this line of reasoning, we should expect that inventors with a partial overlap in their technological profile with the acquiring firm are more likely to stay on. This observation becomes Hypothesis 2.

Hypothesis 2 (H2) *Inventors, who have partial technological overlap with the acquiring firm, are more likely to stay on.*

On the one hand, partially overlapping expertise help the acquiring in absorbing knowledge that is farther from their core competencies, such as biotechnology for established pharmaceutical companies. However, more dissimilar inventors might decide to leave due to difficulties assimilating into the new company. In a separate regression, we also estimate the likelihood to leave inventors with low, mid and high similarity to the acquiring company.

3 Data

For the analysis, we require two primary sources of information: (1) when M&A events took place and which companies were involved, and (2) patents data containing both details on assignees (i.e., typically firm applying for patents) and inventors (i.e., usually employees of those company).

Specifically, for the identification of M&A events and the relevant companies, we rely on Thomson Reuters Recap[3] and Evaluate[4]. For the patent details, we use the disambiguated and geo-referenced patent dataset by Morrison et al. (2017) offering a comprehensive set of patents filed with the United States Patent and Trademark Office (USPTO), European Patent Office (EPO) and Patent Cooperation Treaty (PCT) and cover mainly patents filed in the US, Europe and Japan.

The patent dataset contains 9,290,268 patent Applications filed between 1978 and 2010 and disambiguated inventors and assignees. Additionally, we have data on the geo-location of the inventors at the time of application as well as the International Patent Classification (IPC) of the patent.[5] The disambiguation of inventor names and their location are essential information for our analysis.[6].

Thomson Reuters RECAP contains data on significant deals in the Pharmaceutical sector from 1981 to 2012 and covers 46,135 deals (of various types). RECAP contains detailed information on the parties, dates and types of deals in the biotechnology industry. Specifically, for our purposes, we are interested in the 3,794 outright acquisition events[7]. Similarly, in the Evaluate dataset, we have 6,604 Acquisition events from as early as 1980 up to 2018. Since we need several years after the event to assess retention, we will only use deals up to 1998. Hence we select only acquisitions completed between 1990 and 1998.

The number of acquisition events per year found in the RECAP and Evaluate are shown in Figure 1. We choose this acquisition window because the data after 2005 is

[3]As of 2018 the dataset is sold and maintained by Clarivate, `https://clarivate.com`.

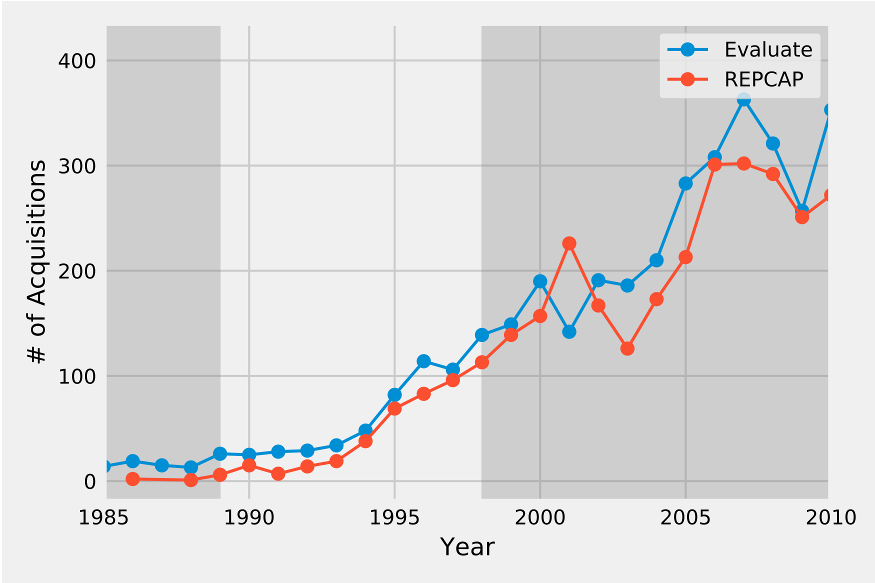
[4]The data has been obtained from `http://www.evaluate.com`.

[5]IPC classes are used in the matching procedure to estimate technological distances among inventors and firms.

[6]The lack of disambiguated author names for more recent patents limits the time coverage of the dataset. In particular, the coverage of the dataset is, however, not complete past 2005, as the sudden drop in patent applications past 2005 suggests. For this reason, we do not rely on any data in the dataset after 2003.

[7]An "Acquisition" is defined in RECAP as: "One company acquires legal control (higher than 50% of voting shares) of the other company, including both assets and liabilities. Acquisitions may be paid with cash or through an exchange of shares from the buying company to the selling company".

Figure 1: Number of acquisition events in the biotechnology industry available in RECAP and Evaluate. The period of interests, 1990 to 1998, is highlighted.



not entirely reliable, and we need several years of inventor activity both before and after the acquisition event. Moreover, most of the M&A activity to absorb the first wave of biotechnologies happened in the Nineties with significant events such as the acquisition of Genentech by Roche in 1990.

We made sure[8] the deals between 1990 and 1998 to be genuine and proper acquisitions (i.e., not only announcement or never materialised) as well as having at least one patent assigned to them several years prior and after the event[9]. Moreover, the matching procedure must find at least one suitable candidate firm and inventor for a treated company to be considered. Given these restrictions, we are left with 48 acquisitions (the list of acquisitions is available in the appendix table 5). We use the remaining data on mergers and acquisitions to identify and exclude companies and inventors who have been acquired or worked for an acquired company from the control group. In this way, we exclude anyone who might have been impacted by mergers or acquisitions apart from those in the treated group.

4 Methodology

We set out to estimate the effect of an acquisition on the probability that an employee at an acquired firm stays with the firm or leaves it to go and work elsewhere. For this purpose, we set up a difference-in-difference regression with matching at both firm and inventor levels.

[8]We do only check firms which do have patents in the relevant period, significantly reducing the number of firms.

[9]In Section 4 we discuss the exact procedure by which we carry out the matching. Specifically, for the main analysis, we require at least one identifiable inventor four years prior, who was active at least one year after the acquisition event.

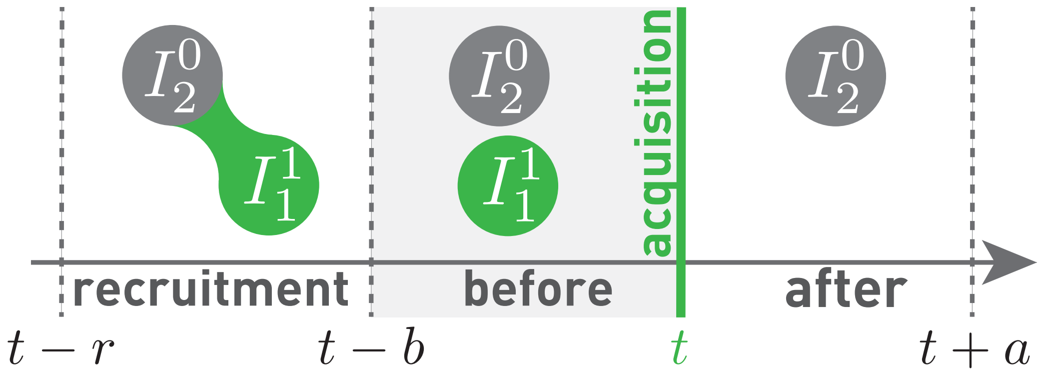
For the difference-in-difference setup, we identify pairs of inventors with similar career characteristics, where one inventor has been subject to an acquisition event and the other not. Explicitly, at a high level, we carry out the following analysis. We match treated (i.e. acquired) and control firms (i.e. never subject of M&A) on patenting rate (i.e. patents per year), age (i.e. years since first patent application) and technological distance (i.e. cosine similarity on IPC). Given this firm-level match, we match inventors working for the control firms with the inventors working for the treated firms, thus obtaining pairs of inventors who work for similar firms and are similar on observable features. With the matched pairs, we then estimate their probability (1) to continue patenting and, if so, (2) if they do so for a third company. A difference in these probabilities between the individuals of the pairs emerging after the acquisition event implies that the treated group has responded to the shock and would support Hypothesis 1. To test Hypothesis 2, that technological distance to the acquirer affects retention; we define four levels of treatment, namely (1) control, (2) high technological similarity to the acquiring company, (3) medium technological similarity to the acquirer, and (4) low technological similarity to the acquirer.

This section describes the matching procedure and how the effect is estimated. The identification of who *is a valid treated employee* is ambiguous for several reasons. First, new employees enter continuously, and, closing in on the actual acquisition event, the event itself might drive the hiring. For example, the acquired company hires new employees in expectation of the takeover or does not hire anyone due to uncertainty. Similarly, not all inventors named on a patent can be unambiguously identified as working for *the treated company*. We call this type of inventors "freelancers" as no exclusive relationship with the target company can be inferred. We find in our dataset several instances of inventors working within a given period intermittently filing patents for unrelated assignees, with no clear signal of affiliation. For example, an inventor listed on four patents assigned to four different companies, thus filing at most 25% of his patents for the focal company.

We address the first concern by setting up a framework to clearly define which inventors we are interested in and which we exclude from the treated group. A more detailed discussion on this setup follows below. Regarding the "freelancers" problem, we have adopted the following convention. Inventors filing exclusively for the company of interest are employees. Suppose in the identification phase; we find that an inventor has filed for multiple companies. In that case, we consider him an employee of a firm if and only if he has filed more than 1/3 of his patents in the relevant period for the focal company. If he files less than 1/3 for the focal company, we drop him from the pool of treated employees and exclude him from the pool of potential controls. This last step helps to alleviate concerns that we might include in the control set "marginally treated" individuals.

Here we introduce the various steps of our methodological approach. The setup defines (1) when inventors are identified as treated or controls and (2) their decisions on staying with the company before and (3) after the event. The event year is denoted by t_E, and the various phases are defined as offsets from this base year. Moreover, we identify treatment at both firm and inventor levels with a superscript, where 1 is treated, and 0 is not treated, and with a subscript, we denote their identity. Accordingly, a treated inventor k is denoted as I_k^1, and an untreated firm h is denoted as F_h^0.

Figure 2: In the "recruitment" phase the matching covariates for the inventors are computed and the matching of the inventors is done (e.g. treated inventor I_1^1 is matched to control inventor I_2^0). In both "before" and "after" periods being active and staying with the company are measured. In this example I_1^1 is active in "before", but we do not see them again in "after" (because they did not file any patents in this period), I_2^0 on the other hand, is active in both periods.



The framework, i.e., the identification and the evaluation periods, is comprised of three distinct phases (see Figure 2). In the first phase, the *"recruitment phase"* in the window $[t_E - r, t_E - b)$, we identify valid treated and control firms as well as inventors. In the second phase, the *"before phase"* covering the period $[t_E - b, t_E)$, we observe the various outcome of interest *before* the event. Finally, in the third phase $[t_E, t_E + a)$, the *"after phase"*, we re-evaluate the same outcome, knowing that the event took place.

As noted in the introduction, studies by both Ravenscraft and Long (2000) and Higgins and Rodriguez (2006), show respectively that firms under stress tend to be acquired and that firms nearing a patent expiration of important compounds are more likely to engage in M&As. For this reason, we think that the crucial "recruitment" phase must be pushed back before the actual event sufficiently to reduce the probability that these firms do not operate in what could be called a "going concern". Ideally, we would have access to financial details to match companies.[10]. This information would allow us to match on financial distress, yielding a match of two firms with a similar propensity to be acquired. To alleviate this concern as best we can with the available information, we recruit firms and inventors at least 3 to 4 years before the event. However, by requiring that companies and inventors be observable for at least four years after they are first recruited to observe their decision to leave the company, we reduce the potential pool of inventors considerably and eliminate young biotech start-ups from our analysis.

In the "recruitment" phase[11]

[10]The financial information about companies that have been acquired a long time ago is no longer available.
[11]the data sets will be described in more detail in Section 3

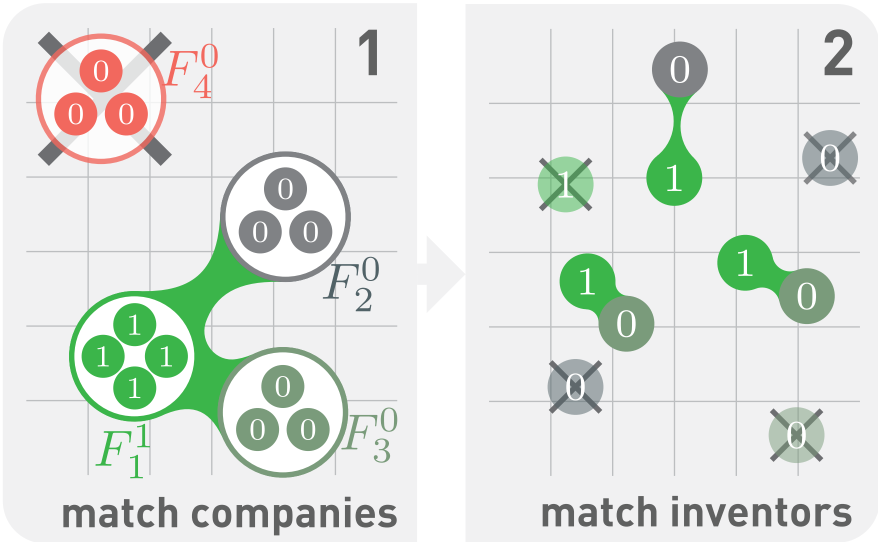
1. companies which are acquired outright in the relevant period are marked as treated and added to the pool of treated firms;
2. these firms are then matched through their names in RECAP and Evaluate with the disambiguated assignees in the patents data sets. By doing so, we obtain matched patents for these Firms and, by extension, the inventors working on these patients (i.e., potential employees);
3. treated and control firms are matched in a onetomany fashion. This means we match a treated firm with possibly multiple control firms if they are "sufficiently" similar. If, however, no adequate match can be found, the firm is dropped;
4. treated inventors working for the acquired firm h (F_h^1) are matched one-to-one with employees working for one of the matched control companies of (F_i^0). The result is a list of treated/control inventor pairs for the analysis in the subsequent stages.

In the "before" phase $[t_E - b, t_E)$ two outcomes for each inventor are observed. First, do they continue filing patents in this period? If they do, we record them as "active". We should note that the cessation of patent production after the event or after the recruitment phase could be caused by inventors moving to administrative or managerial positions but not leaving the company. Those treated and controlled inventors who are active in the "before" period are then classified as either filing patents for the focal company and thus "staying on" or exclusively for a third party and thus "leaving". Since the acquisition did not yet occur, the propensity to leave the company should not be affected. However, as suggested by Ravenscraft and Long (2000) acquisition targets tend to show signs of distress quite sometime earlier.

Finally, we look at the "after" period $[t_E, t_E + a)$, the time interval after the acquisition took place (including the acquisition year). Suppose there would be no effect of the acquisition on the propensity to leave. In that case, we should find that treated, and controls have the same propensity to leave the company, if, on the other hand, we find that treated companies experience a higher level of turnover, we have an indication that the acquisition, if not necessarily caused exit, at least hastened it. Since the acquisition took place at the beginning of this period, the legal identity of the acquiring firm is no longer guaranteed to be the same. In other words, as a consequence of the takeover, the acquired company has either changed its name or has ceased to exist to become a division of the acquiring company. As we track the employer by evaluating the company name on the patent applications, we account for this possibility in the after period by considering an inventor to be "staying on" if she files at least one patent for the acquiring or acquired company or if the company name she files for now has a high string similarity to either of the two. If a match is sufficiently close[12], we check manually if the new assignee name is correct.

[12]To determine in a first pass the string similarity, we compute the Levenshtein distance (Levenshtein, 1966) between the acquiring firm and potential alias and the acquired firm and the potential alias.

Figure 3: The matching of treated to untreated inventors is carried out in two stages; only companies/inventors not too distant in similarity are matched. First, treated companies, e.g. F_1^1, are matched up with untreated companies F_2^0 and F_3^0, one-to-many based on observable features of the firms. In the second stage, the treated inventors (labelled 1) are matched to control inventors (labelled 0) in a one-to-one fashion. Any unmatched inventors are discarded, as is any company for which we do not find a good match.



4.1 Matching Firms

To be able to claim any causality of an acquisition on turnover rates, we need control firms and inventors to compare this rate to.

In this work, we adopt a two-stage matching procedure, whereby, as noted above, we first match treated with control firms and in the second stage, we match treated and control inventors. Conceptually, these two steps are illustrated in Figure 3.

In the first matching step, the *firm matching* step, we try to find companies that are similar to the treated companies we have identified. Since Pharmaceutical companies are R&D intensive and have a high propensity to patent their work, we will make extensive use of patent data to find suitable matches. In the first stage, we identify all treated firms F_i^1 and their patents in the recruitment phase. For each treated firm we obtain its IPC technological profile (τ) at main-group level (e.g. "C08G063"). We obtain a vector of the form $\tau_h = [n_{ipc1}, n_{ipc2}, n_{ipc3}, \ldots]$, where each entry corresponds to the number of patents published in that IPC class by the company. Given their technological profile, we obtain a set of candidate control firms who have published a patent in those fields within the period. In other words, if a treated company F_h^1 filed a patent in IPC main-group `C08G063` in the recruitment phase, we identify all companies, which also filed a patent under `C08G063` in the same period. To make sure that we do not pollute the control set with treated companies, we exclude any company that was or will be subject to any M&A event type listed in RECAP or Evaluate. We will denote this set of potential control firms for firm F_h^1 with $\mathcal{P}_h^0$. For each potential control company in $\mathcal{P}_h^0$ we compute "technological similarity", "age similarity", "patenting rate similarity" and combine these measures into a single "similarity" through a weighted average. For the main analysis, we have weighted technological similarity at 0.5 and the other two similarities at 0.25. Explicitly, we compute the technological distance between a treated company F_h^1 and its potential controls $\mathcal{P}_h^0$ by constructing a tech profile for all companies, as defined above. We define the technological similarity (s_τ) between two profiles τ_h and τ_k using the cosine similarity measure as shown in Eq. (1).

$$s_{hk}^{\tau} = \frac{\tau_h \cdot \tau_k}{||\tau_h||_2||\tau_k||_2} \tag{1}$$

This measure is equal to 1 if the two vectors are identical and 0 if there is no common element (i.e. no shared IPC). The cosine similarity measures the angle between the two vectors defined by the technological profiles.

We then compute the number of patents applied for in the same period (a proxy for the size of the company) and its age (years since the first patent was filed) and obtain a similarity defined by Eq. (2).

$$s_{hk}^{\text{age}} = \frac{|\text{age}_h - \text{age}_k|}{\text{age}_h + \text{age}_k} \tag{2}$$

$$s_{hk}^{\text{patents}} = \frac{|\text{patents}_h - \text{patents}_k|}{\text{patents}_h + \text{patents}_k} \tag{3}$$

These similarities are again 0 if the two firms have the same value and edge closer to 1 the wider the gap between the two is. The final similarity score s_{hk} between F_h^1 and F_k^0 is then given by Eq. (4).

$$s_{hk} = w_\tau s_{hk}^{\tau} + w_{\text{age}} s_{hk}^{\text{age}} + w_{\text{patents}} s_{hk}^{\text{patents}} \qquad w_\tau + w_{\text{age}} + w_{\text{patents}} = 1 \tag{4}$$

If a potential control firm in $\mathcal{P}_h^0$ is 80% similar to the treated firm, it is included in the control set $\mathcal{C}_h^0$ of firm F_h^1, and all its employees become potential controls for the treated employees of F_h^1. The threshold of 80% was chosen to have a large enough sample of inventors but still have a high acceptance threshold. Several other parameters for this value have been tested (i.e. from 50 to 100 in 5% increments), the matching quality as measured by the difference in the propensity to active/stay on before the event increased continuously, as it should if the matching procedure has merit, however at 95% and above only around 100 matches could be found. Thus the choice of 80% represents a balance between matching quality and an excessive rejection rate. As a robustness check, we report the results for the threshold of 90% in the Appendix (Table 6)

4.2 Matching inventors

Similarly to the firm matching, we match treated and control inventors. For a treated inventor I_j^1 working for treated firm F_h^1 we obtain all inventors working for matched control companies C_h^0 and compute several similarity metrics again. We match again on the IPC technological profile (τ_j) for the treated inventor I_j^1 and its controls by using cosine similarity (see Equation (1)). Similarly, we use tenure (i.e. years since the first patent with the company) and patenting activity in the recruitment period to determine similarity (see Equation (2)). These similarities are again aggregated through the same weighted average, and the closest match is chosen as the matched inventor, provided that it is at least 90% similar.

At the end of the two matching steps, i.e. firm matching and inventor matching, we are left with a set of treated-control inventor pairs, which we use in the analysis.

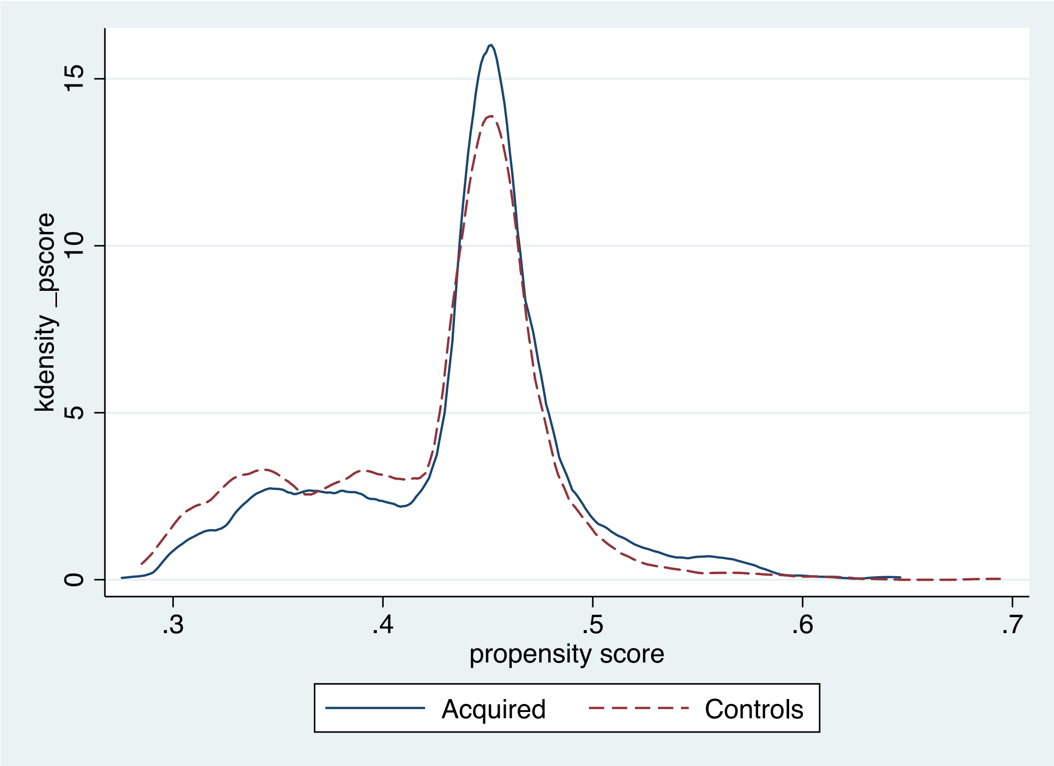
Using standard patent classification systems like the IPC is not without problems, as noted by Arts et al. (2018), as it may fail to identify the similarity between patents correctly. A possible way to improve the estimation of technological distances would be to use a patent's text instead of its proxy, the International Patent Classification (IPC). However, while the IPC approach might not be optimal, it is a commonly used approach in patent research.

5 Results

Now that we have matched treated and control inventors, we want to analyse their patent activity in the "before" and "after" periods. Specifically, we want to test Hypothesis 1: are inventors working for an acquired company more likely to leave than their unaffected controls? We look at whether the two groups differ in their propensity to remain active (i.e. not stop to apply for patents) and second if they do continue their patenting activity into the after-period if they do so for either the acquired company or the acquiring company (i.e. stayed on) or for a third party (i.e. left).

We choose three hyper-parameters r, b and a to define the proposed model completely. These three parameters jointly define the length of the *recruitment* period (r), the length of the *before* period (b) and the length of the *after* period (a). For the main analysis, we set $r = 7, b = 4, a = 4$; we have also carried out the same analysis yielding the same turnover rate for $r = 6, b = 3$ and varying lengths of a. The choice to conduct the recruitment well in advance (i.e. 7 to 4 years before) is conservative. It is conservative since we lose a considerable amount of inventors because, for any additional year after recruitment, the number of active scientists can only decrease. Moreover, recruiting well in advance allows us to mitigate the fact that, on average, acquired firms might experience financial distress or other pre-treatment effects nearing their takeover. We use the hyper-parameter a, the length of the window after, to observe turnover as a means to estimate the effect of the acquisition after the event. So, for example, by comparing the estimate for $a = 3$ with $a = 6$ we can infer if turnover rates have increased in the 3 years that followed or remained unchanged, implying no effect in the last 3 years.

Figure 4: Density plot of propensity score after the match for treated and controls. The propensity is computed as as the predicted probability to be treated given "Age", "Exclusivity" and number of "Patents" of inventors using the `psmatch2` package in Stata.



5.1 Match statistics

Before moving to the actual estimation, we show that the matched inventors on observables (i.e. age, tenure, patents before and technological similarity) are not indicative of treatment status (i.e. work for an acquired company) by showing that the propensity scores given these observables do not differ. In Figure 4, the overlap of the propensity scores across groups confirms the excellent match between inventors working for acquired (treated) and control companies.

Similarly, looking at the distribution of the features on which the companies have been matched on, across treated and control groups as shown in Table 1 we see that they match.

For the chosen window sizes (i.e. $r = 7, b = 4, a = 4$) we have 2,224 inventors in our sample with an equal number of treated and untreated (i.e. 1,112).

An acquiring firm might require the inventors to relocate. Consequently, we would expect several inventors to look for employment with a company located closer to their current location. Unfortunately, in our data, we do not have information on whether the M&A could have required a relocation, something that might be addressed by the information on the location of the research centres of the two companies. In Appendix B we check if, on average, employees who stayed on with the company relocated more

Table 1: Descriptive statistics of characteristics of treated and control and their balance.

	Treated			***Control***		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
Age	7.24	3.64	1,112	7.21	3.56	1,112
Patents	4.10	6.24	1,112	3.35	5.29	1,112
Exclusivity	0.84	0.22	1,112	0.81	0.26	1,112
year	1995.97	2.26	1,112	1995.97	2.27	1,112

often than their peers, who chose to leave. We do not find that inventors working for an acquired firm are more likely to patent in a different location than the control group.

5.2 Inventors' turnover

The dependent variables of interest to test Hypothesis 1 are *active* and *stay on*. We observe each inventor twice in the data set, once in the before period and once in the after-period. Therefore the time subscript t equals 0 before and 1 after. In addition to these two variables, we use several additional covariates to control for patenting activity as listed in Table 2.

We estimate first a censored OLS regression with a difference-in-difference (DiD) specification, where we drop all individuals who did not patent in the given period.[13] The matching procedure discussed above helps us to make sure that we compare two similar groups of inventors working for similar companies. The Difference in Difference specification, assuming that the common trends assumption holds, allows us to estimate the causal effect of acquisitions on turnover rates. The OLS specification serves as our baseline model.

In addition, we estimate a Heckman 2-stage selection model (Heckman, 1979) again with a DiD specification. This approach, combined with the pairwise matching of treated and controls, helps to alleviate concerns that staying with the company can only be observed if the inventors remain active and if the likelihood to remain active could affect our estimate. Specifically, we use the Heckman selection model to control for the censoring, i.e. inventors not being active. If an inventor is not active, we cannot observe whether they stayed on or changed employer.

The Heckman regression requires in the selection equation and exclusion restriction, i.e. a parameter that influences the probability to be observed/censored but does not, in turn, affect the outcome of the main regression. With the selection equation, i.e., in the first stage, the propensity to be observed is estimated, and this propensity is corrected for in the second stage. In other words, the exclusion restriction should affect an inventor's continued activity but not his permanence with the company. We propose the number of years since the first patent (i.e., age) as an exclusion restriction.

[13] We also considered an alternative setting with a restricted set of matched inventors being *both* active in the before and after periods.

Table 2: Variable definitions

Variable	Definition
Active	If the inventor applies for at least one patent in the given period, he is marked as active and inactive otherwise (1=active, 0=inactive)
Stay	If the inventor is active in the period and files any patent for the focal company, he stayed, and the value is 1. If, on the other hand, they file patents exclusively for a third party, they are marked as "not staying on" (= 0)
Year	The year in which the deal took place
Acquired	The value is equal to 1 if the inventor is working for a firm that has been acquired
After	Identifies to which period this observation belongs (i.e. before the deal, or after the deal)
Age	number of years the inventor has been active by the time the deal took place — an inventor filing his first patent in 1990 is five by the year 1995 when their company is acquired
Tenure	number of years the inventor has been with the company at deal year
log(Patents)	The log of the number of patents applied for in the recruitment phase by the inventor
Exclusivity	proportion of patents filed for the company in the recruitment phase by the inventor
High Sim.	Identifies an inventor in the top tercile of technological similarity to the acquiring company.
Medium Sim.	Identifies an inventor in the middle tercile of technological similarity to the acquiring company.
Low Sim.	Identifies an inventor in the bottom tercile of technological similarity to the acquiring company.

The continued activity depends on the time elapsed since the first patent; however in general, permanence with the company does not depend on age.

We argue, therefore, that this variable, only used in the first stage, allows us to identify which inventors are most likely to be observable in the second stage. To address possible concerns regarding the company-specific unobserved effects, we also estimate a third model where we add a fixed effect for every acquired company in addition to deal-year fixed effects.

In formulas, we estimate the following two equations. The selection equation estimates the likelihood of patenting in the next period (i.e., remain active).

$$\begin{aligned}\text{Active}_{it} = {} & \text{Acquired}_i + \text{After}_t + \text{Acquired}_i * \text{After}_t \\ & + \text{Exclusivity}_i + \text{Patents}_i + \text{Age}_i + \text{Year}_i + \text{Company}_i + u_{it}\end{aligned}$$

In the second stage, we estimate the following model:

$$\begin{aligned}\text{StayedOn}_{it} = {} & \text{Acquired}_i + \text{After}_t + \text{Acquired}_i * \text{After}_t \\ & + \text{Exclusivity}_i + \text{Patents}_i + \text{Year}_i + \text{Company}_i + u_{it}\end{aligned}$$

Regression results are shown in Table 3. We estimate in the first stage (probit) the propensity to be active in the early stage. In the second stage, through an OLS or linear probability specification, we estimate the interaction of acquired $\times$ after — the difference-in-difference (DiD) parameter and the main focus of this analysis.

First and foremost, we note that the interaction term acquired $\times$ after, the DiD effect, for the inventor, who stay on, is significant and negative in all three specifications, OLS, simple Heckman, and Heckman with fixed effects.[14] We have a significantly higher number of matched treated and untreated inventors in the Heckman framework. Notably, in the last regression, where we also include year and company-specific dummies, we control for year specific effects (i.e., the general economic and financial conditions) and firm time-invariant characteristics (e.g., location). In our favourite framework — Heckman with fixed effects — we find that inventors working for a treated company are 19.8% less likely to keep on working than the control group in the four years that follow the acquisition event, supporting Hypothesis 1.

In the Heckman framework, we also find that the coefficient of the acquired dummy is equal across groups for both the probability of being active and the probability of leaving the company. This result suggests that the matching procedure has matched treated and controls such that there is no difference in outcomes before the event. This

[14]We also considered an alternative version of the OLS regression with a restricted set of observations where only matched active inventors are considered. Results, which are consistent with the ones reported in Table 3, are available upon request.

Table 3: The effect of firm acquisitions on the probability that inventors of the target company will leave in the four years after the event

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
Main regression, dependent variable Stay						
Acquired	0.355	(1.36)	-0.0145	(-0.65)	0.346	(1.41)
After	-0.140***	(-5.97)	-0.166***	(-6.19)	-0.135***	(-5.41)
Acquired × After	-0.198***	(-5.58)	-0.167***	(-4.58)	-0.198***	(-5.95)
Exclusivity	0.771***	(16.93)	0.863***	(25.47)	0.773***	(18.02)
lpatents	0.104***	(7.19)	0.0981***	(5.11)	0.0912***	(4.39)
Age	-0.00623*	(-2.44)				
Constant	-0.445	(-1.64)	-0.0363	(-0.75)	-0.456	(-1.78)
First stage regression, dependent variable Active						
Acquired			-0.0919	(-1.28)	-0.103	(-1.41)
After			-1.041***	(-14.91)	-1.060***	(-15.03)
Acquired × After			-0.122	(-1.18)	-0.150	(-1.44)
Exclusivity			-0.359***	(-3.34)	-0.400***	(-3.64)
Age			0.0300***	(4.23)	0.0311***	(4.27)
lpatents			1.476***	(37.62)	1.523***	(37.28)
Constant			-1.131***	(-9.28)	-0.305	(-1.82)
athrho			0.0120	(0.16)	-0.0439	(-0.52)
lnsigma			-0.978***	(-59.86)	-1.096***	(-66.91)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	1876		4488		4488	
Log-likelihood	-601.3		-2395.7		-2134.0	
R^2	0.462					
AIC	1650.6		4821.4		4748.1	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The λ in two-step Heckman estimation is not significantly different from 0 at the 95% CI.

result implies that in the DiD estimation, we do not need to rely on the first difference (i.e., the difference before the event).

As we would expect, we find across the board that irrespective of treatment, the two groups are less active in both periods and retention decreases as suggested by the after parameters. The exclusion restriction, i.e. patents parameter, in line with our Hypothesis, shows that being active is strongly positively correlated with continued activity.

We also find that employees having worked exclusively for the acquired company are less likely to leave. The "Exclusivity" parameter is positive and indicates that working exclusively for the company before the event (i.e. "Exclusivity"=1) increases the probability to stay on by as much as 80%. This result reveals that even after controlling for several inventor level features, having demonstrated willingness to work for other companies and thus likely possessing outside options leads to higher turnover.

As a robustness check, we vary the length of the after-period (i.e. a) using 3, 4, 5 and 6 years. Within the first 3 years, we have a DiD effect of -15%, in the first 5 years -21% and at 6 years -22%[15]. This result suggests that the bulk of the effect occurs around the event. However, since we know that potential takeover candidates might experience some financial or productivity distress and patent applications are a delayed signal of activity, we cannot rule out that some of the turnover is due to distress.

The negative impact of acquisitions on the retention of inventors is confirmed when we use more stringent matching requirements (see Appendix Table 6). Similarly, we carried out the Heckman regression considering only treated inventors. That is, we use only the first difference in the DiD specification (see Table 10). We find that, had we not compared the effect against the control group, we would have overestimated the effect. Specifically, we would have obtained an effect of 33%; 13% more than the DiD estimate by omitting the control.

5.3 Technological Overlap

Having seen that acquisitions lead to increased turnover, we look at Hypothesis 2. The literature on M&A (Kapoor and Lim, 2007; Ahuja and Katila, 2001; Cloodt et al., 2006), suggests that acquisitions taking place between companies with partial technological overlap had a higher post-merger innovation and patenting rate.

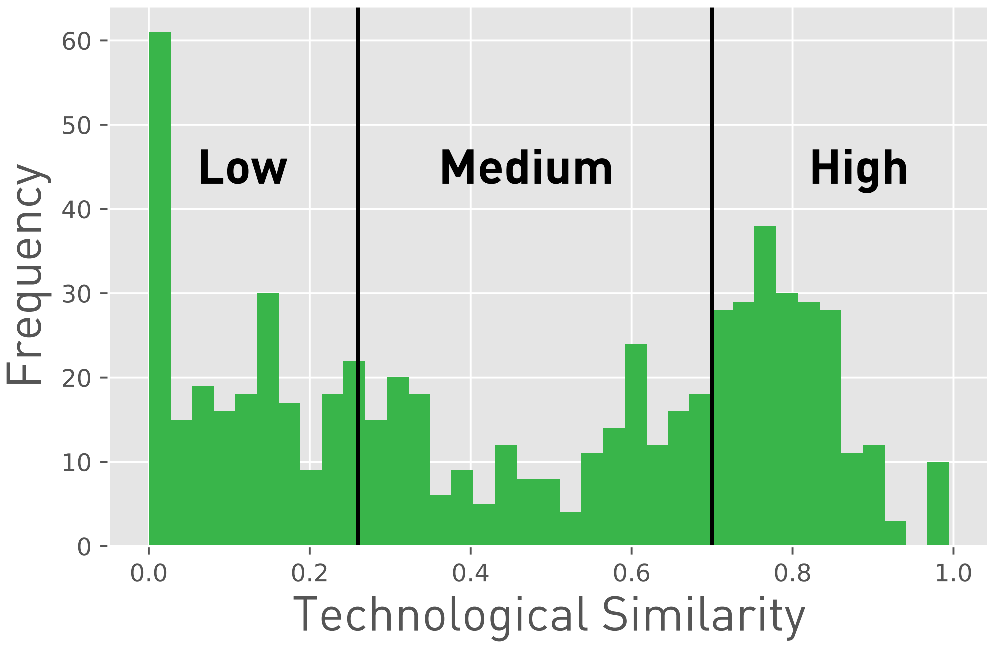
Thus inventors who have partial technological overlap with the acquiring company should be considered valuable sources of future innovation. Conversely, very similar inventors likely duplicate expertise and roles already covered by R&D personnel at the acquiring company and thus might be more likely to leave for this reason. Similarly, inventors working on technologies unrelated to the acquiring company's portfolio might be challenging to integrate and are thus let go. This argument would imply

[15]The regressions specification are identical to the main regression.

that inventors having a partial overlap in their technological expertise are especially valuable. Moreover, one might argue that inventors who are "sufficiently different" from the current technological profile can bring new ideas and skills to the company while still communicating with the resident inventors.

The above notion of "very similar" and "partial technological overall" is vague. Therefore we define and operationalise this notion of technological similarity between inventors and acquiring firms through the previously introduced cosine similarity. Accurately, given the empirical distribution of technological similarities across all treated inventors, we split the inventors into the terciles they belong to (see Figure 5). In other words, we assign the inventors according to their position on the technological similarity spectrum (0 to 1) to be in either in the top, intermediate or bottom terciles.

Figure 5: Distribution of technological similarity (i.e. cosine similarity) between the IPC profile of the acquiring company in the recruitment phase and the IPC profile of the inventor working for the acquired company before the event. The inventors are assigned to either of the three groups: "Low", "Medium" and "High" defined by the terciles of the distribution.



We interpret these three classes as different dosages of the treatment. The introduction of four treatment levels (i.e. Control, High similarity, Medium Similarity, High Similarity) means that instead of the dummy variable acquired$_{it}$ in the previous regression, we have a factor variable with four levels.

The results of this regression are shown in Table 4 (3). In line with Hypothesis 2, we see that inventors at the extreme ends of the similarity spectrum are more likely to leave the company. The effect is weak, however, as indicated both by the regression parameters and the overlapping confidence intervals in Figure 5.

Table 4: The effect of firm acquisitions on the probability that inventors with low, mid and high technological similarity with the acquirer will leave in the four years after the event

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
Main regression, dependent variable Stay						
High Sim.	0.371	(1.42)	-0.0246	(-0.76)	0.358	(1.46)
Medium Sim.	0.328	(1.25)	-0.0225	(-0.74)	0.325	(1.32)
Low Sim.	0.335	(1.27)	0.00873	(0.24)	0.341	(1.37)
After	-0.140***	(-5.96)	-0.167***	(-6.27)	-0.137***	(-5.49)
High Sim. × After	-0.240***	(-4.79)	-0.213***	(-4.10)	-0.242***	(-5.14)
Medium Sim. × After	-0.154**	(-3.25)	-0.114*	(-2.33)	-0.155***	(-3.50)
Low Sim. × After	-0.214***	(-3.50)	-0.188**	(-2.99)	-0.210***	(-3.65)
Exclusivity	0.767***	(16.62)	0.865***	(25.48)	0.773***	(17.79)
lpatents	0.103***	(7.06)	0.102***	(5.33)	0.0934***	(4.49)
Age	-0.00645*	(-2.49)				
Constant	-0.443	(-1.63)	-0.0458	(-0.94)	-0.459	(-1.79)
First stage regression, dependent variable Active						
High Sim.			-0.177	(-1.58)	-0.210	(-1.83)
Medium Sim.			-0.0755	(-0.77)	-0.0689	(-0.68)
Low Sim.			-0.0313	(-0.29)	-0.0460	(-0.42)
After			-1.044***	(-14.93)	-1.064***	(-15.05)
High Sim. × After			-0.222	(-1.41)	-0.228	(-1.43)
Medium Sim. × After			0.00463	(0.03)	-0.0472	(-0.33)
Low Sim. × After			-0.179	(-1.12)	-0.192	(-1.19)
Exclusivity			-0.359***	(-3.33)	-0.399***	(-3.62)
Age			0.0310***	(4.34)	0.0322***	(4.40)
lpatents			1.483***	(37.54)	1.529***	(37.21)
Constant			-1.144***	(-9.33)	-0.349*	(-2.06)
athrho			0.0190	(0.26)	-0.0324	(-0.39)
lnsigma			-0.979***	(-59.92)	-1.097***	(-67.07)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	1876		4488		4488	
Log-likelihood	-599.9		-2389.9		-2129.5	
R^2	0.463					
AIC	1655.8		4825.7		4755.1	

t statistics in parentheses

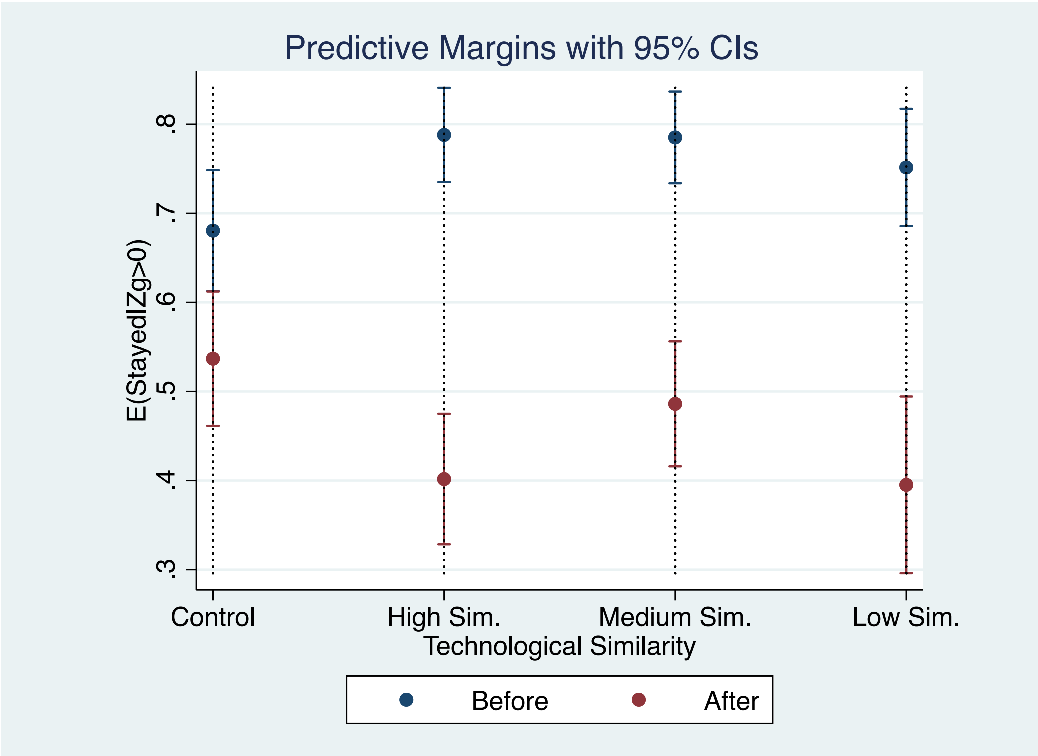
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The λ in the two-step Heckman estimation is not significantly different from 0 at the 95% CI.

As a further robustness check in the Appendix, we perform a placebo test randomly assigning firms to the treated and control groups. As expected, the effect of the acquisitions disappears in this case. Moreover, in a spit regression reported in the Appendix, we find that more experienced inventors are more likely to leave after the acquisition, exacerbating the potential loss of tacit knowledge (see Tables 8 and 9 in the Appendix).

All in all, we find that inventors of acquired companies have a significantly higher probability of leaving in the aftermath of the acquisition. This effect is more substantial for inventors who are not exclusively inventing patents for the target companies and tend to be less pronounced for inventors with an intermediate similarity with the acquiring company.

Figure 6: Marginal Predicted probability to stay on with the company, conditional on being active (i.e. being observable) for the four types of inventors. Inventors in the control group are have not worked for an acquired company. Inventors working for an acquired company are placed in the Low, Medium or High similarity group depending on their technological similarity with the acquiring firm.



6 Final discussion

Firm acquisition is one possible solution for sourcing external knowledge when technological change is fast-paced, and knowledge is complex such as in the biotechnology industry (Carayannopoulos and Auster, 2010). However, to absorb new knowledge, the activities of the newly combined firms must be reorganised (Capron et al., 2001; Karim and Mitchell, 2000; Colombo and Rabbiosi, 2014). The reorganisation of R&D activities can translate into uncertainty and conflicts in the aftermath of the acquisition, and the creative labour force might decide to leave, hampering the potential benefits of the acquisition (Ernst and Vitt, 2000; Paruchuri et al., 2006; Kapoor and Lim, 2007; Fernandez De Arroyabe Arranz and Hussinger, 2018; Arroyabe et al., 2020). As noticed in Colombo and Rabbiosi (2014) among others, the analysis of the impact of the acquisition on R&D performance and inventors' departure is limited by causal ambiguity. Therefore, in this paper we apply a matched difference-in-differences approach to fill this gap. In particular, we focus on the wave of acquisitions of biotech companies in the Nineties as a well know example of acquisitions meant to absorb new knowledge.

From the analysis, it emerges that the departure of inventors is significantly higher following an acquisition. We find that the turnover rate before the M&A event is equal to the control group, but in the 3 to 6 years that follow, this turnover rate goes from 15% to 22% above and beyond the control group. Interestingly, the descriptive analysis of inventor turnover by Ernst and Vitt (2000) finds that one-third of inventors leave their respective companies, a value in line with our finding. We find that having outside options, as measured by the number of patents filed by the inventor for external companies, is a strong indication of turnover. Moreover, senior inventors are more likely to depart. All in all, our results confirm that acquisitions have a significant and persistent negative effect on the turnover of the creative labour force, which might contribute to the reduced R&D productivity after M&A events.

Our analysis also contributes to the literature on the relationship between technological similarity and post-acquisition innovation performance (Colombo and Rabbiosi, 2014). We find that partial technological overlap with the acquiring company does lead to a lower turnover rate. However, when we increase the similarity between the treated and control firms, we find that only the most dissimilar inventors are more likely to leave. We also control if inventors' turnover might be due to induced relocation, but we do not find support for this potential determinant of inventors' departure. We find that relocation is a rare event and that there is no systematic difference across treatment groups and inventors deciding to stay or leave.

These results paint a complex picture of turnover dynamics after an acquisition. On the one hand, turnover is, as expected, higher immediately after acquisitions. On the other hand, those inventors we would assume to be most valuable are also the most likely to leave. Given that R&D employees are considered by the acquiring firms themselves as being especially essential (Ranft and Lord, 2000), our results suggest a causal channel for the reduction of R&D performance after acquisitions is the induced turnover of inventors. Therefore, an acquisition can potentially diminish the value of the acquired target and hamper post-acquisition integration and success.

These findings taken together suggests that if an acquisition target has inventors working exclusively there, their retention is more likely. Still, an increased turnover rate should be expected, especially among those inventors who might possess more dissimilar knowledge. While we do not find that relocation is more common among treated inventors, this option still should be weighted with care since our sample suggests that the vast majority of inventors do not relocate and imposing it could cause an unwanted turnover.

Our findings are of interest for managers and analysts evaluating the success of M&A deals. Specifically, deals with a strong focus on intellectual property, intangible assets, and retention of tacit knowledge are common objectives in complex and highly dynamic technological environments. Further analysis and more information on the particular deal type (e.g. horizontal or vertical integration) could help to identify in which cases

R&D retention is objective and, more importantly, if the post-merger integration in these deals was successful from this perspective.

With this study, we contribute to the literature on post-merger integration, offering additional evidence that acquisitions are accompanied by a higher than expected turnover rate and are subject to complex dynamics. We employ a matching, difference in difference approach in addition to the Heckman selection model to control for various confounding factors. The disambiguated patent and assignees data set allows us to track employment relationships across many companies focusing on our employees of interest (R&D). Our findings are robust to various robustness checks (i.e. varying windows sizes) and the magnitude of turnover we find is in line with Ernst and Vitt (2000), Ranft and Lord (2000) and Carriquiry (2018).

Our analysis has some limitations. We do not use any financial information regarding the acquired or acquiring firms. This limitation is primarily due to the difficulties in obtaining annual reports on these firms, given that they were acquired in the Nineties. We include year and company fixed effects in our analysis to partially overcome this limitation. Moreover, we match treated and control firms well before the event to exclude potential changes in the composition of the pool of inventors in the years preceding the acquisition. Unfortunately, even though we can rely on disambiguated author names and resolved locations, we do not have personal information on the inventors (i.e. actual age, gender, education), which could alleviate concerns in the matching stage. In principle, our proposed methodology can be applied to a more recent M&A events by using a more up to date patent database, thus further strengthening the conclusion. Another promising avenue of research is to consider the arrival of new inventors together with the departure of the creative labour force, as in Arroyabe et al. (2020). Finally, it would be interesting to extend the analysis across sectors, as in Fernandez De Arroyabe Arranz and Hussinger (2018).

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A Data

Table 5: Deals used in the analysis (min 80% similarity requirement satisfied). Deals marked with an asterisk (*) used in the robustness checks with the more stringent matching criterion, i.e, min 90% similarity.

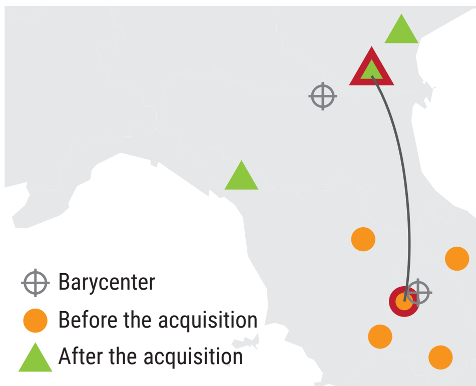
Acquired Firm	Acquiring Firm	Deal Year
Somatogen*	Baxter	1998
Syntex*	Roche	1994
Houston Biotechnology*	Medarex	1996
American Cyanamid*	Wyeth	1994
Scimed Life Systems	Boston Scientific	1994
Cardiovascular Imaging	Boston Scientific	1995
Nycomed	Amersham	1997
Boehringer Mannheim	Roche	1998
Genpharm	Medarex	1997
Calgene*	Monsanto	1997
Yoshitomi*	Green Cross	1997
Ohmeda*	Baxter	1998
Genentech	Roche	1990
Cetus*	Chiron	1991
Nova Pharm	Scios	1992
Applied Biosystems	Applera	1993
Erbamont*	Kabi Pharmacia	1993
Sphinx Pharmaceuticals Corporation*	Lilly	1994
Intramed	Baxter	1994
Kendall Company	Tyco	1994
Kirschner Medical	Biomet	1994
Calgon	Convatec	1994
Vestar*	Nexstar	1994
Glycomed*	Ligand Pharmaceuticals	1995
Pacific Biotech*	Quidel	1995
Heart Technology	Boston Scientific	1995
Cangene*	Apotex	1995
EP Technologies	Boston Scientific	1995
Syntro	Mallinckrodt	1995
Ultracision*	Ethicon	1995
Instent*	Medtronic	1996
Athena Neurosciences	Elan	1996
Symbiosis	Boston Scientific	1996
Novagen	EMD Biosciences	1997
Healthdyne	Respironics	1997
Endovascular Technologies*	Guidant	1997
Perseptive Biosystems	Applera	1997
Nellcor	Mallinckrodt	1997
Ventritex*	St Jude Medical	1997
Microsurge*	Urohealth	1997
Difco Lab	Becton Dickinson	1997
Target Therapeutics	Boston Scientific	1997
Istituto Gentili*	Merck	1997
Sensor Devices*	Heska	1998
Neurex*	Elan	1998
Murex Technologies	Abbott	1998
Seragen	Ligand pharmaceuticals	1998
Pharmachemie	Teva Pharmaceuticals	1998

B The possible effect of inventors' relocation

Do inventors leave because they would have to relocate if they stay on? Unfortunately, we cannot test this hypothesis directly since we do not have information on these inventors' contracts. We can, however, test if the inventors, staying on, moved farther than their leaving peers.

To compute this distance, we need to assign a location to the inventor before and after phases. The patent data set we have used (Morrison et al., 2017) provides for every patent the geographic coordinates of the address the inventors has listed on his application. However, we might not have one unique location for any given inventor if he applied for more than one patent in the period. To assign a unique location to before and after we proceed as follows (see Figure 7).

Figure 7: To estimate the distance between the likely location of the inventor in the before and after phases we compute first the barycenter of the observed locations before (orange circles) and the barycenter after (green triangle). The closes location of the computed barycenter becomes the chosen location and the distance between the two barycenters becomes the "relocation distance".

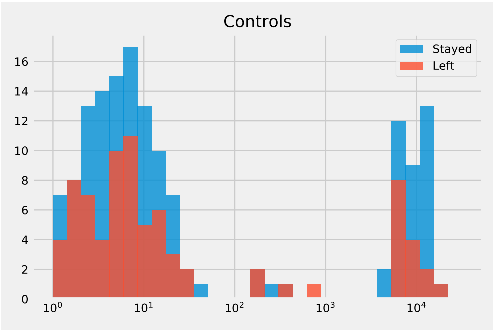


We obtained all locations before the event (orange circles) and all positions after the event (green triangles). To choose the most representative location, we first compute the barycenter, the mean of the location coordinates (depicted as a cross-hair) and select the closest observed location[16]. The "relocation distance" for the inventor from before to after is the great circle distance between these two. Naturally, we can only observe this measure for inventors active in the second period, i.e. inventors who were active after the event.

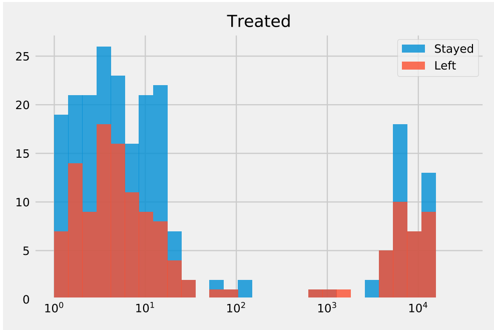
Is there is a difference in the relocation distance between treated and controls? We do not find evidence of a significant difference; in fact, the two groups tend to move the same distances on average. In Figure 8 (a) we see the distribution of the relocation distances by treatment group. The average relocation distance for treated inventors is 204 km and 169 km for their controls. The difference is thus only 35 km, and because the standard deviation is 1160 km and 1100 km, we can reject the hypothesis that there is a difference. Moreover, 82% of treated and 81% of controls are within 10 km of their location in the first period.

[16]The locations representing the cluster also have a dispersion, i.e. they are not in the same place. We also compute the "standard distance", a measure of the dispersion of the points from the barycenter of the cluster (see `http://resources.esri.com/help/9.3/ArcGISengine/java/GP_ToolRef/spatial_statistics_tools/standard_distance_spatial_statistics_.htm`). This value is rarely above 10 km, indicating that the clusters are concentrated in space.

Figure 8: **(a)** Distribution of relocation distances for the control inventors. **(b)** Distribution of relocation distance for treated inventors.



(a)



(b)

Specifically, we find that relocation distances for those who have been acquired net of the relocation distance of those who have left are practically zero (see Figure 8 (b)).

We find that regardless of acquisition status, mobility is rare (likely due to the costs involved). We can say that, while defection might be related to the prospect of having to relocate, relocation across groups is rare enough that it is seldom observed.

C Robustness Checks

C.1 Regression tables with more stringent matching

Tables 6 and 7 are to be compared with tables 3 and 4 in the main text. The only difference is that we consider now a more stringent matching criterion of 90% similarity between treated and control firms (only companies marked with an asterisk (*) in Table 5 are included). In the main text all events in Table 5 are considered with a similarity of 80%.

Table 6: Regression results for the sample with at least 90% similarity.

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
	Main regression, dependent variable Stay					
Acquired	-0.173	(-1.05)	-0.0365	(-1.23)	-0.167	(-1.06)
After	-0.170***	(-6.04)	-0.145***	(-4.27)	-0.152***	(-4.94)
Acquired × After	-0.189***	(-4.02)	-0.196***	(-3.99)	-0.185***	(-4.09)
Exclusivity	0.869***	(16.02)	0.955***	(20.99)	0.878***	(16.79)
lpatents	0.0901***	(4.55)	0.0679*	(2.36)	0.0655*	(2.37)
Age	0.000112	(0.04)				
Constant	0.0591	(0.32)	-0.0180	(-0.27)	0.0947	(0.53)
			First stage regression, dependent variable Active			
Acquired			0.0829	(0.74)	0.0189	(0.16)
After			-1.088***	(-11.07)	-1.117***	(-11.17)
Acquired × After			-0.275	(-1.74)	-0.283	(-1.77)
Exclusivity			-0.340*	(-2.18)	-0.347*	(-2.14)
Age			0.0308**	(3.02)	0.0282**	(2.59)
lpatents			1.598***	(25.13)	1.645***	(25.17)
Constant			-1.278***	(-7.09)	-0.974***	(-4.87)
/						
athrho			-0.139	(-1.14)	-0.140	(-1.20)
lnsigma			-1.066***	(-44.53)	-1.167***	(-48.80)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	932		2042		2042	
Log-likelihood	-231.9		-1049.2		-934.7	
R^2	0.495					
AIC	627.7		2128.3		2061.3	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Regression results for the sample with at least 90% similarity.

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
Main regression, dependent variable Stay						
High Sim.	-0.128	(-0.77)	-0.0639	(-1.43)	-0.120	(-0.76)
Medium Sim.	-0.251	(-1.50)	-0.102*	(-2.35)	-0.239	(-1.50)
Low Sim.	-0.112	(-0.64)	0.0602	(1.33)	-0.112	(-0.68)
After	-0.169***	(-6.04)	-0.143***	(-4.24)	-0.149***	(-4.89)
High Sim. × After	-0.150*	(-2.15)	-0.141	(-1.95)	-0.149*	(-2.24)
Medium Sim. × After	-0.198**	(-2.90)	-0.202**	(-2.85)	-0.195**	(-3.00)
Low Sim. × After	-0.258**	(-3.28)	-0.258**	(-3.13)	-0.244**	(-3.22)
Exclusivity	0.861***	(15.79)	0.957***	(21.14)	0.870***	(16.60)
lpatents	0.0877***	(4.42)	0.0714*	(2.48)	0.0616*	(2.22)
Age	0.000770	(0.27)				
Constant	0.0433	(0.23)	-0.0238	(-0.36)	0.0845	(0.47)
First stage regression, dependent variable Active						
High Sim.			0.156	(0.88)	0.136	(0.73)
Medium Sim.			-0.160	(-0.95)	-0.223	(-1.29)
Low Sim.			0.252	(1.51)	0.169	(0.98)
After			-1.090***	(-11.07)	-1.118***	(-11.17)
High Sim. × After			-0.179	(-0.73)	-0.177	(-0.71)
Medium Sim. × After			-0.160	(-0.68)	-0.167	(-0.70)
Low Sim. × After			-0.477*	(-1.99)	-0.506*	(-2.10)
Exclusivity			-0.340*	(-2.18)	-0.353*	(-2.17)
Age			0.0315**	(3.08)	0.0281*	(2.57)
lpatents			1.602***	(25.09)	1.650***	(25.10)
Constant			-1.286***	(-7.12)	-0.995***	(-4.97)
/						
athrho			-0.151	(-1.23)	-0.154	(-1.30)
lnsigma			-1.073***	(-44.55)	-1.172***	(-48.72)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	932		2042		2042	
Log-likelihood	-226.3		-1039.2		-925.9	
R^2	0.501					
AIC	624.6		2124.4		2059.8	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2 Placebo tests: Random Treatment Assignment

We carry out the following robustness checks to further strengthen the result that the treatment status indicates leaving the company after the event.

- Randomly Assign inventors to treated and control groups, thus removing any link to the treatment status;
- uniformly at random split treated inventors into treated and controls;
- uniformly at random split control inventors into treated and controls

In all three permutations reassigning the inventors using bootstrap sampling (i.e., assignment to treated and control), we find consistently and repeatedly that there is no effect detectable. This means that the treatment control split gives rise to the observed effect and cannot be expected randomly.

C.3 Split regressions for more and less experienced inventors

To verify if the time elapsed since the first patent does affect the likelihood of staying with the company after an acquisition, we run the main regression by splitting two groups of inventors above and below the median time since the first patent (6 years).

We show the results in Table 8 and 9. We find that the likelihood to depart is slightly higher by 3% for more experienced inventors than less experienced ones. This difference is small and barely statistically significant.

Table 8: DiD Regression for inventors with *more* than 6 years of experience (filed first patent) on deal date.

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
	Main regression, dependent variable Stay					
Acquired	-0.169	(-1.12)	-0.0166	(-0.53)	-0.168	(-1.20)
After	-0.128***	(-4.10)	-0.151***	(-4.32)	-0.118***	(-3.73)
Acquired × After	-0.213***	(-4.45)	-0.184***	(-3.70)	-0.213***	(-4.81)
Exclusivity	0.831***	(11.35)	0.917***	(19.22)	0.839***	(12.44)
lpatents	0.118***	(5.77)	0.0854***	(3.70)	0.0997***	(3.96)
Age	-0.00603	(-1.63)				
Constant	0.468*	(2.19)	-0.0584	(-0.89)	0.435*	(2.20)
			First stage regression, dependent variable Active			
Acquired			-0.111	(-0.98)	-0.124	(-1.07)
After			-1.101***	(-10.22)	-1.118***	(-10.24)
Acquired × After			-0.152	(-0.97)	-0.205	(-1.27)
Exclusivity			0.0146	(0.08)	-0.0924	(-0.51)
Age			-0.0181	(-1.73)	-0.0141	(-1.32)
lpatents			1.533***	(25.90)	1.548***	(25.57)
Constant			-0.893***	(-4.39)	0.336	(1.14)
/						
athrho			-0.0196	(-0.20)	-0.0878	(-0.78)
lnsigma			-0.987***	(-43.58)	-1.135***	(-49.62)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	975		2016		2016	
Log-likelihood	-274.1		-1091.2		-923.9	
R^2	0.501					
AIC	838.3		2212.5		2169.8	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: DiD Regression for inventors with *less than or equal* to 6 years of experience (filed first patent) on deal date.

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
			Main regression, dependent variable Stay			
Acquired	0.271	(0.99)	-0.0100	(-0.31)	0.278	(1.13)
After	-0.156***	(-4.36)	-0.156***	(-3.77)	-0.119**	(-3.08)
Acquired × After	-0.176***	(-3.34)	-0.149**	(-2.78)	-0.174***	(-3.63)
Exclusivity	0.814***	(12.13)	0.817***	(16.83)	0.813***	(13.50)
lpatents	0.116***	(4.92)	0.0869**	(2.69)	0.0638	(1.76)
Age	0.0269	(1.33)				
Constant	-0.694	(-1.92)	0.0382	(0.52)	-0.433	(-1.42)
	First stage regression, dependent variable Active					
Acquired			-0.0908	(-0.96)	-0.0881	(-0.92)
After			-1.072***	(-11.24)	-1.089***	(-11.35)
Acquired × After			-0.106	(-0.76)	-0.130	(-0.92)
Exclusivity			-0.423**	(-2.95)	-0.433**	(-2.96)
Age			0.349***	(7.77)	0.338***	(7.48)
lpatents			1.600***	(27.08)	1.660***	(26.79)
Constant			-2.832***	(-9.47)	-2.251***	(-6.55)
/						
athrho			-0.101	(-0.85)	-0.245	(-1.71)
lnsigma			-0.968***	(-40.26)	-1.117***	(-41.22)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	901		2472		2472	
Log-likelihood	-260.8		-1255.2		-1096.7	
R^2	0.496					
AIC	859.6		2540.3		2563.5	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.4 Regression without controls

To highlight that the use of the difference-in-difference methodology is indeed needed to avoid an overestimation of the effect we show here the regression following the specification in the main text, but removing the treated × period interaction. With this specification we look at the effect size had we not used a treated/control specification.

Specifically, we estimate the following equations using only treated inventors, i.e., inventors working for an acquired firm.

$$\text{Active}_{it} = \text{After}_t + \text{Exclusivity}_i + \text{Patents}_i + \text{Age}_i + \text{Year}_i + \text{Company}_i + u_{it}$$

In the second stage, we estimate the following model:

$$\text{StayedOn}_{it} = \text{After}_t + \text{Exclusivity}_i + \text{Patents}_i + \text{Year}_i + \text{Company}_i + u_{it}$$

Table 10: Regression without controls: Simple difference (before vs after).

	(1) OLS		(2) Heckman (2S)		(3) Heckman (2S), FE	
Main regression, dependent variable Stay						
After	-0.338***	(-12.44)	-0.323***	(-9.88)	-0.328***	(-10.45)
Exclusivity	0.823***	(12.62)	0.829***	(14.48)	0.829***	(13.07)
lpatents	0.106***	(5.20)	0.0945***	(3.51)	0.0889**	(3.15)
Age	-0.00378	(-1.11)				
Constant	0.160	(1.77)	-0.00707	(-0.09)	0.157	(1.74)
First stage regression, dependent variable Active						
After			-1.213***	(-13.66)	-1.288***	(-13.88)
Exclusivity			-0.0685	(-0.38)	-0.241	(-1.27)
Age			0.0392***	(3.49)	0.0388***	(3.35)
lpatents			1.564***	(24.87)	1.640***	(24.46)
Constant			-1.612***	(-8.06)	-0.523	(-1.86)
/						
athrho			-0.0693	(-0.66)	-0.0772	(-0.71)
lnsigma			-0.992***	(-39.52)	-1.047***	(-41.66)
Deal Year Effects	Yes		No		Yes	
Company Fixed Effects	Yes		No		Yes	
Observations	803		2244		2244	
Log-likelihood	-297.3		-976.3		-900.4	
R^2	0.390					
AIC	688.5		1974.6		1922.9	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$