The Impact of Acquisitions on Inventor Turnover in the Pharmaceutical Sector

Luca Verginer  
IMT School for Advanced Studies Lucca  
AXES  
luca@verginer.eu

Federica Parisi  
IMT Lucca  
AXES  
federica.parisi@imtlucca.it

Jeroen Allard van Lidth de Jeude  
IMT Lucca  
NETWORKS  
jeroen.vanlidth@imtlucca.it

Massimo Riccaboni  
IMT- INSTITUTE FOR ADVANCED STUDIES LUCCA  
AXES  
massimo.riccaboni@imtlucca.it

Abstract

Acquisitions are employed in various industries for numerous reasons (e.g. vertical/horizontal integration). For research and development (R&D) intensive industries, where intellectual property plays a central role, the acquisition and retention of codified (i.e. patents) and tacit knowledge (i.e. employees) is of major concern and is arguably an integral part of the motivation for the manoeuvre. The transfer of ownership of patents and other codified intellectual property can be formalised as part of the deal, however the retention of key employees embodying valuable tacit knowledge and potential future innovation is less certain. As argued elsewhere, while not all employees are relevant for the success of the takeover, R&D personnel is certainly among the most valuable. In this work we estimate therefore how likely an inventor working for an acquired company is to leave. Employing a matching and difference in difference approach we find that inventors affected by an acquisition are 30% less likely to stay with the company then the control group. Moreover we find that relocation even after the takeover are rare, indicating that inventors even after an acquisition are not likely to move, however we do not find a difference between acquired and not acquired inventors or those that stay or leave.
The Impact of Acquisitions on Inventor Turnover in the Pharmaceutical Sector

February 28, 2019

Abstract

Acquisitions are employed in various industries for numerous reasons (e.g. vertical/horizontal integration). For research and development (R&D) intensive industries, where intellectual property plays a central role, the acquisition and retention of codified (i.e. patents) and tacit knowledge (i.e. employees) is of major concern and is arguably an integral part of the motivation for the manoeuvre. The transfer of ownership of patents and other codified intellectual property can be formalised as part of the deal, however the retention of key employees embodying valuable tacit knowledge and potential future innovation is less certain. As argued elsewhere, while not all employees are relevant for the success of the takeover, R&D personnel is certainly among the most valuable. In this work we estimate therefore how likely an inventor working for an acquired company is to leave. Employing a matching and difference in difference approach we find that inventors affected by an acquisition are 30% less likely to stay with the company than the control group. Moreover we find that relocation even after the takeover are rare, indicating that inventors even after an acquisition are not likely to move, however we do not find a difference between acquired and not acquired inventors or those that stay or leave.

A firm’s post Mergers and Acquisition’s (M&A) performance depends on its ability to exploit the assets and capabilities of the target company. Crucially for Research & Development (R&D) intensive industries, this does not only entail tangible but also intangible assets. It follows therefore that intellectual property both in codified form (e.g. patents) and tacit knowledge (i.e. key employee know-how) must be managed with care so as not to jeopardize the success of the maneuver. In fact, Gottweis and Prainsack (2006) find that employee turnover is a major reason for M&A failure, with reportedly up to three quarters of these deals failing (King et al., 2004). Specifically we look at the Pharmaceutical industry which saw a rush of M&As in the Nineties\(^1\). This sector is an exceptionally R&D intensive sector,

\(^1\)Mergers and Acquisition’s (M&A) deals in 1999 involving a US companies were worth well
with Pharmaceutical Researchers and Manufacturers of America (2012) claiming that as much as 17% of sales are devoted to R&D, compared to the US industry average of 4% (Danzon, Epstein, and Nicholson, 2007). The importance of patents and Intellectual Property (IP) is therefore a clear priority. Inventors, the employees behind these innovations, represent by extension future production of patents and as such their retention is also important. This is especially relevant if we assume that these employees have relevant tacit knowledge and contribute to difficult to replicate “socially complex knowledge” (Barney, 1991), i.e. firm capabilities which emerge from rich social interactions. As Coff (1997) puts it, you don’t want the source of your competitive advantage to simply “walk out the door”.

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) stays with the company and continue to produce patents, however this is not the only alternative they have. The alternatives we focus on in this work is (2) that they continue their patenting activity, but do so for a third party unrelated to the M&A or (3) retire. However there are various intermediate degrees with which an affected inventor could respond, he could (4) reduce his patenting activity and transition to a different role where he no longer applies for patents, thus for our patent based approach he would disappear, but still stay with the company.

The extant literature addresses turnover and related performance issues as they related to top management (e.g. Hambrick and Cannella (1993), Haveman (1995), and Halebian et al. (2009)), turnover in general (Carriquiry, 2017) and to a lesser degree the impact of M&As on R&D personnel (Ernst and Vitt, 2000). However, Fernandez De Arroyabe Arranz and Hussinger (2018) looks at the defection of rate of inventors following an M&A event and find 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. That study does however not rely on any matching or Difference in Difference methodology and so a casual link is not established. In contrast, the present study focuses first and foremost on estimating the defection rate itself, which we find to be 30%, a much higher proportion, and in line with the numbers found by Ernst and Vitt (2000) and Ranft and Lord (2000).

We want contribute to this discussion by providing further evidence that M&As have a detrimental effect on retention of inventors.

Specifically, we want to answer the question, whether an acquisition has a negative effect on inventor retention. We look specifically at acquisitions in the Life Sciences (mainly biotechnology and pharmaceuticals) for two reasons. First, it represents an R&D intensive sector and hence relevant for our analysis on retention of employees and intellectual property and second, in the Nineties, the pharmaceutical sector has experienced an increased rate of M&A events, ranging from mergers between large pharmaceuticals companies to acquisitions of Biotechnology start-ups, in excess of 500 Billion USD (Danzon, Epstein, and Nicholson, 2007), highlighting the economic importance of the practice.
In the same period Tomasello et al. (2017) find that research alliances in general and the pharmaceutical sector in particular were on the rise. This results shows that firms were eager to pool resources to be at the cutting edge of R&D, and M&As are natural next step in pooling resources.

Moreover, excluding the most recent deals gives us the possibility to look at the M&A effects on the long run. Finally, this choice allows us to avoid relying on the latter part of the patent applications, whose coverage might incomplete due delays in data availability.

Note that we do 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, however we will also use the term M&A in connection to theoretical results in the literature, as well as in the exclusion of firms involved in mergers. We do this to sidestep several difficulties we might encounter when considering also Mergers. First, by only considering Acquisitions there is a clear indication of which entity will have control and that no new legal entity might emerge from the transaction\(^2\). Second, the relationship of acquired and acquiring allows us to identify the party in the deal, which is arguably most likely to be affected by changes, i.e. the acquired firm.

The remainder of this work is organized as follows. In Section 1 we discuss the extant literature on employee turnover and M&As. In Section 2 we introduce the various datasets. The empirical strategy is presented in Section 3 as well as the various steps involved in our matching procedure. In Section 4 the regression results are shown. Finally, we discuss the results and their importance, how they fit in with the extant literature and possible improvements in Section 6.

1 Acquisitions and turnover

There is a rich literature on the motivations of M&A and their impact on both stock returns, employee turnover and the post-merger integration. Here we offer an overview of the literature on employee turnover and the various caveats regarding both the motivation for M&As as well as the type of companies, which are most likely to be involved.

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, Epstein, and Nicholson, 2007; Higgins and Rodriguez, 2006; Ravenscraft and Long, 2000). Higgins and Rodriguez (2006), analyzing pharmaceutical firms in the Nineties, finds that companies with expiring patents and declining internal productivity are more likely to engage in M&As. The rational behind this proposed mechanism is that expiring patents free up production and R&D

\(^2\)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.
capacity quickly and fixed and sunk cost assets (i.e. employees and factories) can be used to enhance the impact of an acquired company which has a viable compound but lacks productive and marketing capabilities.

M&A can lead to positive stock performance as Higgins and Rodriguez (2006) finds. M&As that were 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, with the caveat that the acquired firms were more likely to experience financial difficulties (Danzon, Epstein, and Nicholson, 2007). With respect to the financial standing of companies engaging in M&As. In particular Ravenscraft and Long (2000) find that acquired firms tend to experience negative stock returns up to 18 months prior to takeover.

In this work we take a “knowledge base view of the firm”\(^3\) and argue that among the various motives, in addition to the acquisition of codified intellectual property (i.e. patents) the retention of tacit knowledge held by employees is an important factor for R&D intensive industries. Consequently, retention of employees involved in R&D efforts as witnessed by their patent applications, is a desirable outcome.

Hambrick and Cannella (1993) finds evidence that the departure of important employees was an important 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 and argues that retention of key employees is difficult to get right in acquisitions.

With respect to turnover 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 likely 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 top executives were the most likely to leave and 22.7% R&D personnel left on average. However, he also finds in accordance with our hypothesis that R&D personnel is considered to be the most important class of employees to be retained. Specifically, Ernst and Vitt (2000), focusing on acquisitions in general in the US and Germany, finds that indeed inventors tend to leave their company.

As noted by Carriquiry (2017) the disruptive nature to the firms by a major managerial intervention is cause to believe that it might have an overall negative effect on the turnover rate. Changing routines, managerial hierarchies and the added stress of uncertainty the decision of employees to leave a company. Hobman et al. (2004) for example argue that this increased pressure can cause turnover. 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 difference in the “culture”

\(^3\)In accordance with the definition of “knowledge base view of the firm” given by Grant (1996) a firm is considered to be a vehicle to organize tacit and complex social knowledge held by individuals to create products and services.
or managerial could trigger a reevaluation. What is clear also from a meta analysis of turnover in general by Griffeth, Hom, and Gaertner (2000) is that the motivations for turnover are many and varied, but in the case of strong shocks it is argued that higher than average turnover is to be expected. If a company is acquired by an external firm which might require the inventors to relocate, we would also expect several inventors to look for employment with a company located closer to home. 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 information on the location of the research centers of the two companies. What we can control for is however how “exclusive” an inventor is, specifically the proportion of patents filed for his company. We should expect, that if an inventor perceives the M&A to be a shock or adverse to his career prospects, he would look outside opportunities, and having collaborated with several outside companies his ability would be known to those companies as well as having already shown his ability to switch employer. So far we have argued that retention of inventors is important and focused on the reasons a given inventor might leave, however the employment relation will only continue if it is also in the best interest of the acquiring firm. Possible reasons for terminating inventors after an acquisition are varied, starting with duplication of expertise, which are already covered by the acquiring firm or the acquiring firm abandons a research area completely. This last point would be reasonable, given the finding by Zhu (2018) that acquiring firms tend to sell of acquired patents right after the event. However, it is still a valid assumption that the acquiring firms would normally not want to immediately decimate its newly acquired inventors, arguably valuable assets, but phase them out slowly. Inventors on the other hand as argued above might see the shock as a driving force to change employer. So while there are certainly both forces at work, defection as a choice by the inventor himself is likely a major driver.

We look therefore in this work at the specific question: “Are inventors working for acquired companies more likely to leave for a third company?”. Specifically we use a matching Difference in Difference approach along with a Heckman selection model. We match treated (inventors working for acquired companies), with controls (never worked for treated companies) an

It is this stream of research that we want to contribute to and provide further evidence that acquisitions are negative shocks and important employees respond by leaving the company and take their know-how with them.

2 Data

For the analysis we require two main 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. Firm applying for patents) and their inventors (i.e. Employees of the company).
Specifically, for the identification of M&A events and the relevant companies we rely on the following datasets, “Thomson Reuters Recap”\textsuperscript{4} and “Evaluate”\textsuperscript{5}. Moreover, we use the disambiguated and geo-references patent Dataset by Morrison, Riccaboni, and Pammolli (2017) offering a comprehensive set of patents filed with the USPTO, EPO and PCT.

The “patent data” contains 9,290,268 patent Applications filed between 1978 and 2010 as well as disambiguated inventors and Assignees. Additionally, we have data on the geo-location of the inventors at the time of application as well as the IPC classification of the patent. The latter we use in the matching procedure to estimate technological distances among inventors and firms. A high-level overview of the data available and the relationships between assignees, patents and inventors are illustrated in Figure 1. The coverage of the dataset is however not complete past 2005, as the sudden drop in patent applications past 2005 suggests (shown in Figure 2). For this reason we do not rely on any data in the dataset after 2003. This restricts our analysis to smaller time period. It is however necessary to omit this part of the data, so as not to falsely classifying an inventor as leaving only because we do miss observations.

“Thomson Reuters RECAP” contains data on major deals in the Pharmaceutical sector from 1981 to 2012 and covers 46,135 deals (of various type). RECAP contains detailed information on the parties, dates and types of deals in the Pharmaceutical sector. Specifically, for our purposes we are interested in the 3,794 outright acquisition events\textsuperscript{6}. 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 chose only deals falling within the 1990 and 1998 interval. After checking manually\textsuperscript{7} that the deals in the 1990 and 1998 to be genuine and proper acquisitions (i.e. not only announcement or falling through) as well as having sufficient patents assigned to them several years prior and after the vent\textsuperscript{8}. we are left with 135 acquisitions to work with. This implies that we have 135 acquired firms. 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. In this way we exclude from our set of potential controls anyone who could have been influenced by an acquisition. The number of acquisition events per year found in the RECAP and Evaluate are shown

\textsuperscript{4}As of 2018 the dataset is sold and maintained by Clarivate. \url{https://clarivate.com}

\textsuperscript{5}The data has been obtained from \url{http://www.evaluate.com}

\textsuperscript{6}An “Acquisition” is defined in RECAP as: One company acquires legal control (greater 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”.

\textsuperscript{7}We do only check firms which do in fact have patents in the relevant period, greatly reducing the number of firms.

\textsuperscript{8}In Section 3 we discuss the exact procedure by which we carry out the matching. Specifically for the main analysis we require at least 1 identifiable author 4 years prior, who was active at least one year after the acquisition event.
Figure 1: The patent database offers information on several types of relationships between patents, Assignees, inventors and Paten Classifications. With the dataset we are able to identify which inventors worked for which Assignees (i.e. Companies) and under what IPC these patents have been classified.

Figure 2: patent Applications filed per year available in the dataset.
3 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 for a third firm. For this purpose we set up a differences in difference style regression with matching at both firm and inventor level.

Specifically, 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 IPCs). Given this firm level match we proceed to match inventors working for the control firms with the inventors working for the treated firms, thus obtaining pairs of inventors which work for similar firms and are themselves similar on observables. With the matched pairs we then proceed to estimate their probability (1) to continue patenting and (2) and if so which firm is the assignee. A difference in these probabilities emerging after the acquisition event implies that the treated group has responded to the shock. In this section we will describe in detail how the matching is done and how the effect is estimated.

The identification of who is a valid treated employee is ambiguous for several reasons. First, new employees enter constantly and closing in on the actual acquisition event, the reason for hiring might be driven by the event itself. For example, new employees are hired in expectation of the takeover or employees are not hired 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 clear employment relation can be inferred. We find in our data 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 is named on 4 patents assigned to 4 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. With regards to the “freelancers” problem we have adopted the following convention. Inventors filing exclusively for the company of interest are clearly employees. If in the identification phase we do find that an inventor has filed for multiple companies we consider him to be an employee of a firm if and only if he has filed more than 1/3 of his patents in the relevant period for focal company. If however 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 pollute the control set with “partially treated” individuals.

Here we introduce the various phases in the framework. 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 level with a superscript, where 1 is treated and 0 not treated, and with a subscript we denote their identity. Accordingly, a treated inventor $k$ is denoted as $I^1_k$ and an untreated firm $h$ is denoted as $F^0_h$.

![Figure 4: 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 $I^0_2$). 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 him again in “after”, $I^0_2$ on the other hand is active in both periods.](image)

The framework, i.e. identification and the evaluation periods, is comprised of three distinct phases (see Figure 4). In the first phase, the “recruitment phase” in the window $[t_E - r, t_E - b)$, valid treated and control firms and inventors are
identified. In the second phase, the “before phase”, we observe the various outcome of interest before the event, and covers the period \([t_E - b, t_E]\). Finally, in the third phase \([t_E, t_E + a]\), the “after phase”, we evaluate the same outcome again, 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. It is for this reason that 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. This would allow us to match on financial distress, yielding a match of two firms that have 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 prior to the event. However, by requiring that companies and inventors be observable for at least 4 years after they are first recruited to observe their decision to leave the company we reduce the potential pool of inventors considerably as well as eliminating small and young bio-tech startups from our analysis.

In the “recruitment” phase several things happen:

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 REPAC and Evaluate with the disambiguated Assignees in the patents dataset. By doing so we obtain matched patents for these Firms and by extension the inventors working on these patents (i.e. potential employees).

3. Treated and control firms are matched in a one to many fashion. This means that we match a treated firm with possibly multiple controls 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 \(h(F^1_h)\) are matched one to one with employees working for one of the matched control companies of \((F^0_i)\). The result is a list of treated/control inventor pairs which are the focus of the analysis in the subsequent stages.

In the “before” phase (i.e. \([t_E - b, t_E]\)) 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 cessation of patent production after the event, could simply be caused by inventors being placed in administrative or managerial positions, but in fact do not leave the company. Those inventors, both

---

9the datasets will be described in more detail in Section 2
treated and controls, 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 take place, ideally 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 some time earlier.

Finally, we look at the “after” period (i.e. \([t_E, t_E + a]\)), the time interval after the acquisition took place (including the acquisition year). If there would be no effect of acquisition on the propensity to leave 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 the exodus, 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 the acquired company as a consequence of the takeover has either changed name or has ceased to exist and become a division of the acquiring company. To account for this possibility in the after period an inventor is considered to be “staying on” if he files at least one patent for the acquiring or acquired company or if the company name he files for now has a high string similarity to either of the two. If there is a match which is sufficiently close\(^\text{10}\), we check manually if the new assignee name is correct.

\[ 3.1 \text{ Matching Firms} \]

To be able to claim any causality of an acquisition on defection rates we need to construct a valid set of control Firms and inventors to compare the defection rate against.

In this work we adopt a two stage matching procedure, whereby as noted above we first match treated con control firms and in the second stage we match treated and control inventors. Conceptually, these two steps are illustrated in Figure 5.

In the first matching step, the firm matching step, we try to find companies which 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 good matches. In a 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 (\(\tau\)) at main-group level (e.g. “C08G063”). We obtain a vector of the form \(\tau_{h} = [n_{ipec1}, n_{ipec2}, n_{ipec3}, \ldots]\), 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

\(^{10}\)To determine in a first pass, the string similarity we compute the Levenshtein distance (Levenshtein, 1966) between the acquiring firm and the potential alias and the acquired firm and the potential alias.
First, treated companies (e.g. $F_1^1$) are matched up with untreated companies (e.g. $F_2^0$ and $F_3^0$, one to many) on their covariates. In the second stage, the treated inventors (labeled 1) are matched to control inventors (labeled 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.

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 $F_1^1$ with $P_0^F$. For each potential control company in $P_0^F$ 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 with 0.25. Specifically, we compute the technological distance between a treated company $F_1^1$ and its potential controls $P_0^F$ by constructing a tech profile for all companies, as defined above. We define the technological similarity ($s_{\tau}$) between two profiles $\tau_h$ and $\tau_k$ using the cosine similarity measure as shown in (1).

$$s_{hk} = \frac{\tau_h \cdot \tau_k}{||\tau_h||_2||\tau_k||_2}$$ (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 two similarity edges closer two one the more elements the two vector share and the closer the number of patents filed in these IPCs are.

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

\[
\begin{align*}
  s_{hk}^{\text{age}} &= \frac{|\text{age}_h - \text{age}_k|}{\text{age}_h + \text{age}_k} \\
  s_{hk}^{\text{patents}} &= \frac{|\text{patents}_h - \text{patents}_k|}{\text{patents}_h + \text{patents}_k}
\end{align*}
\]  

(2)

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 \( F_1^h \) and \( F_0^k \) is then given by (4).

\[
s_{hk} = w_\tau s_{hk}^{\tau} + w_{\text{age}} s_{hk}^{\text{age}} + w_{\text{patents}} s_{hk}^{\text{patents}} \quad w_\tau + w_{\text{age}} + w_{\text{patents}} = 1
\]

(4)

If a potential control firm in \( P_0^h \) is 90% similar to the treated firm, it is included in the control set \( C_0^h \) of firm \( F_1^h \) and all its employees become potential controls for the treated employees of \( F_1^h \).

### 3.2 Matching inventors

In a similar fashion to the firm matching we match treated and control inventors. For a treated inventor \( I_j^1 \) working for treated firm \( F_1^h \) we obtain all inventors working for matched control companies \( C_0^h \) and compute again several similarity metrics. We match again on the IPC technological profile (\( \tau_j \)) 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 first patent with 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 as noted by Arts, Cas-siman, and Gomez (2018) is not without problems, as it may fail to correctly identify similarity between patents, a possible way to improve the estimation of technological distances, would be to use a patent’s text instead of its proxy the IPC classification. However, while the IPS approach might not be optimal, but it is a commonly used approach in patent research.

### 4 Estimation and results

Now that we have matched treated and control inventors we want to estimate how they behaved in the “before” and “after” periods. Specifically, we want to assess if 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).

For the actual estimation we still have 3 hyper parameters to choose, namely \( r, b \) and \( a \). 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 fix \( (r = 7, b = 4, a = 4) \), however we have carried out the same analysis yielding the same defection 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, due to the fact that 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 experience financial distress nearing their takeover. We will also use the hyper parameter \( a \), the length of the window to observe defections 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 defection rates have increased in the 3 years that followed or remained unchanged, implying no effect in the last 3 years. In fact, we do find that

Before we move to the actual estimation, we show that the matched inventors on observables (i.e. age, tenure, patents before) are not indicative of treatment status (i.e. work for an acquired company) through a Logit regression. In other words we show that there is no bias in the those variables across groups. The results, for the particular parameter choice of \( (r = 7, b = 4, a = 4) \) shown in Table 1, suggest that neither of the covariates is predictive of treatment. This provides some measure of confidence that the matching procedure has worked. For the main chosen windows in the main analysis of \( (r = 7, b = 4, a = 4) \) we have 1,214 inventors in our sample with an equal number of treated and untreated (i.e. 607). Of these 370 are active in the after period.

The dependent variables of interest for the analysis are active and stay on. We observe each inventor twice in the dataset, once in the before period and once in the after period. This means that the time subscript \( t \) is equal to 0 before and 1 after. In addition to these two variables we use several additional covariates to control for age and patenting activity as listed in Table 2.

We estimate a Heckman 2 stage selection model (Heckman, 1979) with a Difference in Difference specification. This, in addition to the pairwise matching of treated and controls, should help us to alleviate several concerns. We use the Heckman selection model to control for the censoring, i.e. inventors not being active. If an inventor is not active, we are not able to observe whether she stayed on or defected to a third company. The matching on observables helps us to make sure that we compare two similar groups of inventors, working for similar companies. The Difference in Difference approach, assuming that the common trends assumption is not violated, allows us to estimate the effect of acquisitions on defection rates of the treated population.

The Heckman regression requires in the selection equation an exclusion restric-
Table 1: Propensity to be treated on covariates. The Logistic regressions shows that the propensity to be treated is not correlated with any of the covariates the inventors have been matched on.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>active</td>
<td>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)</td>
</tr>
<tr>
<td>stay on</td>
<td>If 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 he file patents exclusively for a third party he is marked as “not staying on” (= 0)</td>
</tr>
<tr>
<td>deal year</td>
<td>The year in which the deal took place</td>
</tr>
<tr>
<td>acquired</td>
<td>The value is equal to 1 if the inventor is working for firm that has been acquired</td>
</tr>
<tr>
<td>after</td>
<td>Identifies to which period this observations belongs (i.e. before the deal, or after the deal)</td>
</tr>
<tr>
<td>age</td>
<td>Number of years the inventor has been active by the time the deal took place — an inventor applying for patent in 1990 and his company is acquired in 1995 is 5 years old</td>
</tr>
<tr>
<td>tenure</td>
<td>Number of years the inventor has been with the company at deal year</td>
</tr>
<tr>
<td>patents</td>
<td>The number of patents applied for in the recruitment phase by the inventor</td>
</tr>
<tr>
<td>exclusivity</td>
<td>Proportion of patents filed for the company in the recruitment phase by the inventor</td>
</tr>
</tbody>
</table>

Table 2: Variable definitions
tion, i.e. a parameter which 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. 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 re-
striction should affect an inventors continued activity, but not his permanence with
the company. We propose as an exclusion restriction the number of patents filed
in the recruitment period. The continued production of patents is an indication of
momentum, in the sense that having patented more it is more likely to continue this
activity. Highly productive individuals might also be more valuable for the company
but their proven expertise mean also that they have more outside options and could
defect if they so choose. We therefore argue that this variable, only used in the first
stage, allows us to identify which inventors are most likely to be active.

We control in the second stage for the “exclusivity” of the inventor to his em-
ployer, by controlling for proportion of patents he has assigned to the focal company
over all patents he has applied for. This means that an employee with exclusivity
equal to 1 has filed patents exclusively for the focal company, and 0 otherwise. Note,
that due to the “freelance rule” discussed in Section 3, all exclusivity values are at
least 1/3.

We estimate in the first stage (probit) the propensity to be active using the spec-
fication shown in Equation (5). In the second stage, an OLS or linear probability,
we estimate the interaction of acquired × after — the DiD parameter and main focus
of this analysis.

\[
\text{active}_{it} = \beta_0 + \beta_1 \text{acquired}_{it} + \beta_2 \text{after}_{it} + \beta_3 \text{acquired}_{it} \times \text{after}_{it} + \beta_4 \text{age}_{i} + \beta_5 \text{age}^2_{i} + \beta_6 \text{tenure}_{i} + \beta_7 \text{tenure}^2_{i} + \beta_8 \text{exclusivity}_{i} + \beta_9 \text{deal year}_{i} + u_{it}
\]

\[
\text{stayed on}_{it} = \beta_0 + \beta_1 \text{acquired}_{it} + \beta_2 \text{after}_{it} + \beta_3 \text{acquired}_{it} \times \text{after}_{it} + \beta_4 \text{age}_{i} + \beta_5 \text{age}^2_{i} + \beta_6 \text{patents}_{i} + \beta_7 \text{deal year}_{i} + u_{it}
\]

The results of this regression are shown in Table 3. We note first and foremost
that the interaction term acquired × after, the DiD effect, for the scientist, who stay
on, is significantly negative. In other words we do find that according to the OLS
estimate, inventors working for a treated company are 27% less likely to keep on
working than the control group in the 4 years that follow the acquisition event. We
also find that acquired is equal across groups for both the probability to be active
and the probability to leave the company. This means that the matching procedure
<table>
<thead>
<tr>
<th>Stage 2</th>
<th>stayed on</th>
</tr>
</thead>
<tbody>
<tr>
<td>stayed</td>
<td></td>
</tr>
<tr>
<td>acquired</td>
<td>-0.00719</td>
</tr>
<tr>
<td>after</td>
<td>-0.0939**</td>
</tr>
<tr>
<td>acquired × after</td>
<td>-0.269***</td>
</tr>
<tr>
<td>age</td>
<td>-0.0285</td>
</tr>
<tr>
<td>age^2</td>
<td>0.00137</td>
</tr>
<tr>
<td>tenure</td>
<td>-0.0124</td>
</tr>
<tr>
<td>tenure^2</td>
<td>0.000570</td>
</tr>
<tr>
<td>exclusivity</td>
<td>0.841***</td>
</tr>
<tr>
<td>Constant</td>
<td>0.237**</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage 1</th>
<th>active</th>
</tr>
</thead>
<tbody>
<tr>
<td>acquired</td>
<td>-0.00725</td>
</tr>
<tr>
<td>after</td>
<td>-0.906***</td>
</tr>
<tr>
<td>acquired × after</td>
<td>-0.331**</td>
</tr>
<tr>
<td>age</td>
<td>0.189***</td>
</tr>
<tr>
<td>age^2</td>
<td>-0.00793***</td>
</tr>
<tr>
<td>patents</td>
<td>0.353***</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.119***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Deal Year Effects</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>athrho</td>
<td>-0.409***</td>
</tr>
<tr>
<td>Insigma</td>
<td>-1.040***</td>
</tr>
</tbody>
</table>

| Observations            | 2,428                      |
| Censored                | 1,377                      |

_t_ statistics in parentheses

* _p < 0.05_, ** _p < 0.01_, *** _p < 0.001_

Table 3: Regression Results of the 2 stage Heckman regression. The first stage estimates the propensity to be active and the second stage, the main focus, is on OLS on the probability to leave the company. A linear probability model.
has been able to match treated and controls such that there is no difference in outcomes before the event. This is an important result, since it implies that in the difference in difference estimation we do not need to rely on the first difference (i.e. 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.

As a robustness check we vary the length of the after period (i.e. \(a\)) and use 3, 4, 5 and 6 years. Within the first 3 years we have a DiD effect of -25\%, in the first 5 years -31\% and at 6 years 32\%\(^{11}\). This results suggests that the bulk of the effect takes place around the event. However, since we know that potential takeover candidates might experience some sort of financial or productivity distress and patent applications are a delayed signal of activity, we cannot rule out that some of the defections are not caused by the acquisition but are due to distress.

5 Difference in relocation propensity

We have observed that treated inventors tend to leave their company with a higher propensity then their untreated counterparts. A possible reason to leave the company could be the aversion of inventors to relocate. To test this explicitly we obtain the location of the inventor before the event (i.e. 4 years before) and compare it with the location after (i.e. 4 years after) and test the following hypothesis.

- Is there a difference in the distance traveled between treated and untreated?
- For treated is the distance traveled lower for inventors who leave the company?

Before we can compute these measures we need to assign a location before and after to the inventor. The patent dataset we have used (Morrison, Riccaboni, and Pammolli, 2017) gives for every patent the geographic coordinates of the address the inventors has listed on his application. However, for any given author we might not have one unique location 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 6). We obtain all locations before the event (orange circles) and all locations after the event (green triangles). In order to choose the most representative location we first compute the barycenter, the mean of the location coordinates, which is depicted as a cross hair and choose the closest observed location\(^{12}\). The “relocation distance”

\(^{11}\)The regressions are all equal to the main regression using an after window of 4. All other parameters have similar magnitude and significance.

\(^{12}\)The locations representing the cluster have also a dispersion, i.e. they are not in the same place. We compute also 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_
Before the acquisition

Barycenter

After the acquisition

Figure 6: To estimate the distance between the likely location of the inventor before and after 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”.

for the inventor from before to after is the great circle distance between these two. Naturally we can only observe this measure for the inventors which are active in the second period, i.e. inventors which were active after the event.

Figure 7: (a) Distribution of relocation distances by treatment group. (b) Distribution of relocation distance for treated inventors divided by whether they stayed on with the company or left for a third company.

With regards to our first hypothesis, that there is a difference in the relocation distance between treated and controls we do not find evidence in support, in fact the two groups tend to move the same distances on average. In Figure 7 (a) we see the distribution of the relocation distances by treatment group. The average relocation distance for treated inventors is 204 kilometers and 169 for their controls.

ToolRef/spatial_statistics_tools/standard_distance_spatial_statistics_.htm). This value is rarely above 10 km indicating that the clusters are quite concentrated in space.
The difference is thus only 35 km and in light of the fact that the standard deviation is 1160 km and 1100 km respectively we can safely reject the hypothesis that there is a difference. Moreover 82% of treated and 81% of controls can be found within 10 km of their location in the first period.

Similarly the difference in relocation distances for those who have been treated but left the company are indistinguishable from those that left the company (see Figure 7 (b)).

The strong result that we obtain, is that regardless of an acquisition mobility is rare, likely due to the cost involved in such a decision. What we can say is that, while defection might be related to the prospect to have to relocate, relocation across groups is rare enough that it is rarely observed.

6 Discussion and Conclusions

From the analysis it emerges that the turnover rate is significantly higher following an acquisition. In fact, we find that the turnover rate before the event is equal to the control group, but in the 3 to 6 years that follow this turnover rate goes from 26% to 31% above and beyond the control group. Surprisingly, the descriptive analysis of inventor defection by Ernst and Vitt (2000) finds that one third of inventors leave their respective company, a value in line with our finding. Moreover we have found that regardless of treatment status and the choice to stay with the company after the event, inventors tend to resist relocation and stay in 80% of the cases within 10 km of their original location.

R&D employees are considered by the firms themselves as being especially important (Ranft and Lord, 2000), our results suggesting a high turnover can have detrimental effects on the post-merger performance and integration. We do find also that the degree to which an inventor works exclusively for the focal company is strongly indicative of continued work there. Conversely this means that inventors, who have worked for external companies before and in line with our initial hypothesis have more “outside options” and tend to defect at a higher rate. This findings suggests that if an acquisition target has inventor working exclusively there, their retention is easier. This result should however be considered in light of the fact the young researchers and possibly less productive researchers are very likely to be “exclusive” to the company, however their value to the acquiring firm might not be the same as more seasoned inventors. Moreover the strong tendency of inventors to stay in their current location regardless of any external intervention, suggests that for a takeover to be successful in retaining these high skill individuals relocation should be weighted with caution.

These findings are of interest for managers and analysts evaluating the success of M&A deals. Specifically those deals that have a strong focus on intellectual property and retention of tacit knowledge. Further analysis and more information on the particular deal type (e.g. interested only in equipment, vertical integration) could
help to identify in which cases R&D retention is an 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 defection rate. Our analysis has several strengths. 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 dataset allows us to track employment relationships across many companies focusing on our employees of interest (R&D).

However, we did not use any financial information regarding the acquired or acquiring firms. This is in large part due to the difficulties to obtain annual reports on these firms, given that they were active in the Nineties. And similarly we do not have personal information on the inventors (i.e. real age, gender, education) which could alleviate several concerns in the matching stage. Our proposed methodology could be applied to a more recent vintage of M&A events by using a more up to date patent database, possibly reaching into 2018 and thus further strengthen the conclusion. However, the finding is robust to various checks (i.e. varying windows sizes) and the magnitude of turnover is in line with Ernst and Vitt (2000), Ranft and Lord (2000) and Carriquiry (2017).

In summary, with this work we have shown that inventors, crucially important, for the success of firms operating in the R&D intensive pharmaceutical sector, respond to acquisitions by leaving. This effect is reduced for inventors who did not patent for another company. However, the defection rate is high at 30%, a number which is confirmed by several other studies using different data sources and methods. What is clear, is that inventors might in fact vote with their feet and leave to the detriment of the acquiring firm.

References


Danzon, Patricia M., Andrew Epstein, and Sean Nicholson (June 2007). “Mergers and acquisitions in the pharmaceutical and biotech industries”. In: Managerial and Decision Economics 28.4-5, pp. 307–328. ISSN: 01436570. DOI: 10.1002/mde.1343.


Morrison, Greg, Massimo Riccaboni, and Fabio Pammolli (May 2017). “Disambiguation of patent inventors and assignees using high-resolution geolocation data”. In: Scientific Data 4, p. 170064. ISSN: 2052-4463. DOI: 10.1038/sdata.2017.64.


