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The impact of biotech acquisitions on inventor productivity

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ABSTRACT

This study explores the impact of acquisitions on the productivity and retention of inventors, which is critical for shaping effective corporate acquisition strategies and innovation management. We analyze the patenting activity of 15,318 inventors involved in 1,375 acquisitions of biotech firms from 1990 to 2010. Employing a staggered difference-in-differences approach, our findings reveal a 13.5% increase in inventor turnover and a 35% decrease in citation-weighted patent productivity subsequent to acquisitions. The decline in productivity is particularly pronounced among the remaining inventors, especially those whose expertise closely matches the technological focus of the acquired company. Conversely, experienced inventors with skills that complement the acquiring firm's R&D focus tend to maintain or even enhance their productivity post-acquisition. These results illuminate the varied effects of acquisitions on inventor productivity and emphasize the importance of strategic alignment in planning acquisitions.

1. Introduction

Acqui-hires are strategic solutions increasingly used by established companies such as Microsoft, Roche, and Google to absorb knowledge in emerging technology areas.[1] Clearly, from the perspective of the acquiring company, the success of takeovers depends crucially on whether the company can retain talented inventors after the acquisition (Boyacıoğlu, Özdemir, & Karim, 2024). However, from a societal standpoint, the implications of acqui-hiring for innovative undertakings remain largely controversial. In certain circumstances, incumbent companies deliberately acquire innovative start-ups to suppress their innovative capacity and reduce future competition—so-called killer acquisitions (EU, 2024). Even when the goal is to absorb knowledge and increase the productivity of R&D, it is important to recognize that tacit knowledge—deeply embedded in individual inventors and their social interactions—is difficult to codify or transfer. Acquisitions interrupt this flow of knowledge and can jeopardize R&D productivity if inventors leave the company or fail to adapt to the new organizational structure. Therefore, the intended and unintended consequences of acquisitions can either support or hinder inventors' productivity.

By examining the retention and productivity of inventors after an acquisition, this study applies the Knowledge-Based View (KBV) of the firm to analyze whether and how firms manage and retain critical knowledge assets during corporate restructuring. The KBV posits that a firm's ability to create, integrate, and manage knowledge is a key source of competitive advantage (Grant, 1996; Spender & Grant, 1996). In particular, the KBV provides a useful framework for understanding the challenges and opportunities posed by acquisitions (Carayannopoulos & Auster, 2010; Park, Howard, & Gomulya, 2018). In R&D-intensive sectors, innovation success depends on both codified intellectual property (e.g., patents) and tacit knowledge (e.g., the expertise of inventors). We focus on the biotechnology sector, which is highly dependent on knowledge-intensive resources and has experienced significant M&A activity, especially between 1990 and 2010 (Riccaboni & Pammolli, 2002; Tomasello, Napoletano, Garas, & Schweitzer, 2017). During this period, new biotechnology firms (NBFs) founded since the 1970s became prime acquisition targets for large pharmaceutical companies seeking access to cutting-edge knowledge to replenish their product pipelines and replace lapsing patent protection (Béraud, Drajac, & Thomas, 2020; Orsenigo, Pammolli, & Riccaboni, 2001; Pammolli, Riccaboni, & Spelta, 2021).

This study focuses exclusively on outright acquisitions, in which one company fully absorbs another, as opposed to weaker forms of M&A such as partial acquisitions or mergers. This focus allows for a clear identification of the knowledge source targeted by the acquisition and

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[1] See, e.g., Financial Times (2024) and The Economist (2024) for artificial intelligence.
[2] See Ornaghi (2009) for an analysis of the impact of mergers on innovation in the pharmaceutical sector.

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the associated inventors, who are most likely to experience significant organizational change.[2]

On the one hand, acquisitions can provide start-ups and smaller companies with resources, infrastructure, and access to broader R&D networks, potentially increasing innovation capacity (Danzon, Epstein, & Nicholson, 2007; Fernandez De Arroyabe Arranz & Hussinger, 2018). On the other hand, takeovers can lead to both intended and unintended interruptions of innovation processes. For example, Kapoor and Lim (2007) and Hitt, Hoskisson, Ireland, and Harrison (1991) point out that acquisitions often lead to declines in inventors' productivity due to organizational restructuring, misalignment of resources, and reduced autonomy. In extreme cases, killer acquisitions are carried out specifically to suppress innovation and eliminate competitive threats (Cunningham, Ederer, & Ma, 2021).

Retaining the human capital of the target company is a decisive factor for post-acquisition success, particularly in knowledge-intensive sectors. Inventors, who are key drivers of innovation, are often at risk of leaving after a takeover. Ranft and Lord (2000), in particular, emphasize the importance of retaining R&D staff, as they hold the tacit and socially embedded knowledge essential for innovation (Barney, 1991). Studies by Hambrick and Cannella (1993) and Carriquiry (2018) show that turnover increases when employees perceive acquisitions as disruptive to their career prospects or to the corporate culture. Retention challenges are especially acute when the technological or managerial cultures of the acquiring and acquired firms are misaligned (Brede, Gerstel, Wöhrmann, & Bausch, 2024; Haveman, 1995).

The literature on R&D productivity following M&A presents mixed findings. For instance, Ornaghi (2009) and Seru (2014) document a decline in patent production and quality after takeovers, whereas Hussinger (2010) suggests that technological complementarities may mitigate these negative effects. While knowledge similarity has been shown to support knowledge integration (Ahuja & Katila, 2001), both excessive similarity and excessive dissimilarity can pose challenges (Cloodt, Hagedoorn, & Van Kranenburg, 2006; Kapoor & Lim, 2007).

Whereas most prior research assesses acquisition impacts at the firm level or relies on coarse proxies of R&D productivity, our study tracks over 15,000 individual inventors and directly measures their mobility and patent productivity.[3] This fine-grained approach enables us to assess not only whether productivity declines but also why, and for whom, it does. Moreover, we adopt a causal inference framework to isolate the impact of acquisitions on inventor retention and R&D productivity from other confounding factors.[4] Specifically, we employ a staggered difference-in-differences design.

This approach allows us to control for factors such as the pre-existing likelihood of a firm becoming an acquisition target and the intrinsic productivity of inventors. Our results contribute to the literature by providing robust causal evidence on the impact of acquisitions on R&D performance. Using this framework, we estimate a 13.5% turnover rate among inventors in the five years following an acquisition, consistent with previous studies (Ernst & Vitt, 2000; Ranft & Lord, 2000). Additionally, we find that citation-weighted patent production declines by 35%, indicating a significant reduction in innovation quality and impact post-acquisition. These productivity losses are more pronounced among inventors who remain with the acquiring firm, underscoring the challenges of effective knowledge absorption.

Importantly, we show that these negative effects are moderated by several factors: the knowledge specificity of the acquired firm's knowledge base, the similarity between the knowledge bases of the acquiring and acquired firms, and uncertainty about future R&D performance. To explore these dynamics, we develop hypotheses about how individual inventor characteristics, organizational factors, and strategic choices shape post-acquisition retention and productivity outcomes.

By focusing on the biotechnology sector, our study offers a unique perspective on how firms in R&D-intensive industries address the challenges posed by acquisitions. We introduce novel moderators—such as inventor exclusivity and inventor-firm technological similarity—that have not previously been jointly examined in causal studies on post-acquisition performance. Our work contributes to both the theoretical development of the KBV and the practical management of knowledge assets during M&A events.

2. Background and hypotheses

In this paper, we adopt a KBV of the firm, drawing on Grant 's (1996) definition of a firm as an entity that orchestrates the tacit and complex social knowledge of individuals to produce goods and services. The KBV posits that the competitive advantage of firms results primarily from their ability to manage and utilize knowledge, especially in innovation-driven industries.

Beyond acquiring codified intellectual property (e.g. patents, which provide formal and easily transferable legal protection for innovations), retaining employees' tacit knowledge (unwritten, experience-based, and context-specific knowledge) is crucial for the success of acquisitions. However, it is widely recognized that acquisitions can disrupt the knowledge of the acquired company's workforce, as shown by Kapoor and Lim (2007) and Arnold, Milligan, Moon, and Tavakoli (2023). The seminal work by Coff (1997) on human resource management and tacit knowledge strongly supports this perspective, contending that retaining key employees poses a significant challenge during takeovers. Hambrick and Cannella (1993) finds evidence that the departure of critical employees was a significant predictor of poor post-merger performance. Furthermore, Carriquiry (2018) discovered that the disruptive nature of acquisitions could result in an overall negative impact on turnover rates.

Takeovers could mean a dramatic change in the target company's R&D organization and a reduction in the autonomy and independence of inventors who may leave the company. Several studies revealed that top executives and management are prone to departing from the firm following an acquisition (Haveman, 1995; Krug & Hegarty, 1997; Xiao & Dahlstrand, 2023). Similarly, Ranft and Lord (2000) highlighted that R&D personnel are among the most critical employees to retain. Indeed, shifts in routines and managerial structures, coupled with uncertain career trajectories (Hobman, Jones, Callan, Bordia, & Gallois, 2004), can prompt inventors to opt for departure from a company. Holtom, Mitchell, Lee, and Inderrieden (2005) contend that events like M&As catalyze employees to reassess their career and life objectives. For instance, an employee contemplating leaving beforehand might interpret the M&A as a signal to take action. Likewise, disparities in managerial cultures could prompt a reassessment.

The departure of inventors following an acquisition often leads to reduced R&D productivity. As highlighted in the KBV literature, inventors typically collaborate in teams, and reconfiguring these teams post-acquisition is a time-consuming process that can negatively affect individual productivity. Departing inventors face the challenge of integrating into new teams. At the same time, those who remain may have to adapt to disrupted routines and struggle to collaborate effectively within the new organizational structure, often feeling the absence of their former colleagues' contributions. Kapoor and Lim (2007) observed a lasting negative impact on inventor productivity in the semiconductor industry due to acquisitions. However, Kapoor and Lim (2007) also notes that few studies have focused on the individual inventors' perspective, mainly because tracking their long-term performance is challenging.

These observations and results lead us to formulate the following Hypothesis 1:

[3] See Table 1 in the appendix for an overview of the literature on the effects of M&A on innovation.

[4] This methodological approach is novel in this field, as highlighted in the Appendix Table 1.

Hypothesis 1 (*H*1)**.** Acquisitions are traumatic events that increase the likelihood of inventors leaving the company (H1.1). Acquisitions have a lasting negative effect on the productivity of inventors (H1.2).

Our study builds on this by examining the extent to which the disruption of knowledge is caused by inventors leaving the company or by a decline in productivity among the remaining inventors. In our conceptual framework, some important factors can mitigate the negative impact of acquisitions on R&D productivity.

2.1. The moderating effect of uncertainty about R&D productivity

According to the KBV of the firm, the most valuable knowledge is specific to the firm. Therefore, the biggest challenge for knowledge seekers in takeovers is to correctly assess the value of the ideas of the acquired inventors. If there is a discrepancy between the knowledge seekers' assessment and the inventors' expectations, individual characteristics influence the inventors' reactions to acquisitions, as some of the best employees may leave the acquiring company (Arnold et al., 2023). Kaul, Ganco, and Raffiee (2024) identify some of the most important factors for potential disagreements between inventors and acquiring companies about the future potential of their ideas. In general, target firms are better positioned to assess the value of their knowledge sources. According to the theoretical framework of Kaul et al. (2024), when there is significant uncertainty about the potential future productivity of the target company's inventors, it is more likely that the inventors will leave the acquiring company, as they may have more problems securing access to resources in the new organization (Kim, 2022). This is particularly important for young inventors, as it is known that the productivity of inventors changes over the course of the so-called inventor life cycle (Jones, 2010; Kaltenberg, Jaffe, & Lachman, 2023). Young inventors do not yet have an established record of producing patents, which makes it more difficult for the acquiring company and the market to assess their innovation potential. Therefore, uncertainty about investments in human capital can jeopardize the productivity of R&D after an acquisition by misallocating resources and human capital investments. To better assess the moderating role of uncertainty on the potential of inventors' ideas in our analysis, we measure inventors' age as the number of years since their first patent application, reflecting their professional experience.

On the basis of these premises we can postulate the following research hypotheses about the moderating role of uncertainty.

Hypothesis 2 (*H*2)**.** Younger inventors are more likely to leave the acquiring company (H2.1). Less experienced inventors who stay will suffer a greater loss of R&D productivity (H2.2).

To test H1 empirically, we need a clear measure of whether an inventor has left the acquired or acquiring firm. We capture this with a binary variable, "Left", which equals 1 if an inventor does not appear on any new patent applications for the acquiring or acquired firm beyond a given year, and 0 otherwise. More details in the Data Section.

2.2. The moderating role of knowledge specificity

A second source of potential disagreement between acquired inventors and the acquiring company arises from *knowledge specificity*, defined as "the extent to which knowledge is unique to the firm that creates it" (Carayannopoulos & Auster, 2010). Highly specific knowledge is deeply embedded in the target company's routines and culture, making it difficult for external observers—such as managers of the acquiring firm—to accurately assess its potential value.

We capture knowledge specificity through an inventor's *exclusivity*, measured as the proportion of patents the inventor filed for the target firm relative to total patents before the acquisition. *High-exclusivity* inventors, whose patenting activities are almost entirely tied to the target firm, have particularly firm-specific knowledge. *Low-exclusivity* inventors, by contrast, have filed patents for multiple firms, indicating knowledge that is more broadly applicable and easily transferable.

Because high-exclusivity inventors more likely rely on the routines, teams, and organizational culture that supported their past success, they may find it harder to adapt to a new corporate setting post-acquisition. If the acquiring firm fails to recognize or integrate their niche expertise effectively, friction can arise, hampering their R&D output. Paradoxically, despite this risk of lower productivity, these inventors may have fewer external opportunities—because their skills are so tightly interwoven with the target's processes, outside employers may undervalue their firm-specific knowledge and they have fewer contacts.

By contrast, low-exclusivity inventors may have more industry-specific or generalizable expertise and broader professional networks, making them more likely to exit if the post-merger environment proves unappealing. Should they stay, however, their adaptability can foster a smoother transition, leading to less disruption in productivity.

Taken together, these considerations suggest that while high-exclusivity inventors might be "locked in", the challenge of transferring their deeply embedded knowledge to a new organizational context can depress their productivity. Meanwhile, some high-exclusivity inventors may find a new employer that better aligns with their specialized skills, thus avoiding a productivity drop.

Hypothesis 3 (*H*3)**.** Exclusive inventors are less likely to leave the acquiring company (H3.1). Exclusive inventors who stay will suffer a greater R&D productivity loss (H3.2).

2.3. The moderating role of knowledge similarity

While we emphasized the importance of retaining inventors and explored potential factors that might prompt an inventor to leave, it is crucial to acknowledge that the continuation of the employment relationship is contingent upon being mutually beneficial for both the inventor and the acquiring firm.

The rationales behind terminating inventors post-acquisition are diverse, ranging from redundant skill sets already present within the acquiring firm to discontinuing research in specific areas altogether. This latter point aligns with the observation by Zhu (2018) that acquiring firms often divest acquired patents shortly after the acquisition event. Similarly, Ornaghi (2009) outlines comparable adverse effects on R&D productivity in the pharmaceutical sector resulting from mergers.

However, according to the KBV of the firm, it is reasonable to assume that an acquiring company would not want to abruptly dispense with its newly acquired inventors, arguably valuable assets, preferring to phase them out slowly. On the contrary, as previously mentioned, inventors might perceive this upheaval as an impetus to seek employment elsewhere. This could be particularly pertinent for inventors lacking technological commonalities with the acquiring firm, as their expertise may be deemed more valuable in the marketplace than within the boundaries of the merged entity. Similarly, inventors whose knowledge do not align with the core competencies of the acquiring firm may opt to depart for organizations where their skills are more applicable and appreciated.

Retention is especially vital for inventors with technological overlap with the acquiring firm, which we measure as the number of Common IPC—the number of shared International Patent Classification subclasses between the inventor's and acquiring firm's patents. Similar metrics have been used in prior studies, such as Ahuja and Katila (2001), who examine technological overlap in the context of mergers, and Hussinger (2010), who highlight its importance for post-acquisition R&D integration.

Regarding the impact of expertise duplication, technological affinity, and the subsequent performance of firms post-merger, research by Kapoor and Lim (2007), Ahuja and Katila (2001), and Cloodt et al. (2006) indicates that the highest levels of patenting output and

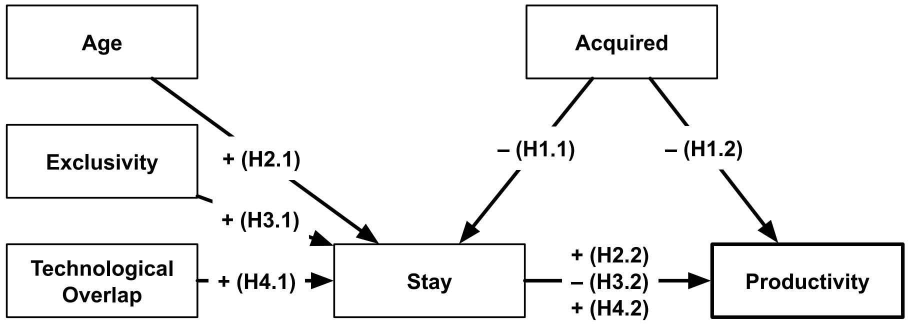

Fig. 1. A conceptual map linking all hypotheses to show their impact on the retention of inventors and the productivity of R&D.

innovation occur when the technological profiles of the acquiring and acquired firms are aligned. Conversely, as emphasized in the literature on KBV of the firm, a very low level of knowledge similarity is associated with reduced productivity (Park et al., 2018). In the context of biotech acquisitions, the necessity for technological overlap is arguably less critical than in large-scale pharmaceutical mergers, as noted by Ornaghi (2009). Additionally, when inventors operate within the same patent classes, acquiring firms are better positioned to assess the potential of new ideas.

Following this line of reasoning, we should expect that inventors with a technological profile that overlaps with the acquiring firm are more likely to stay and remain productive after an acquisition.

Hypothesis 4 (*H*4)**.** Inventors with higher knowledge similarity with the acquiring firm are more likely to stay on (H4.1). Inventors with similar knowledge who remain are more productive (H4.2).

To summarize the hypotheses presented above, we illustrate them in a conceptual map shown in Fig. 1.

In general, takeovers have a negative impact on human capital retention and patent production. The negative consequences of acquisitions are mitigated for experienced inventors and inventors with a high degree of knowledge similarity to the acquiring firm. If experienced and similar inventors stay, they tend to remain productive. Conversely, inventors whose knowledge was very specific to the target company are less productive if they stay after the takeover, as their knowledge is more difficult to absorb.

3. Data

For our analysis, we require two types of information: (1) detailed acquisition events and (2) a comprehensive patent dataset containing details of assignees, inventors, and citations. Our study on inventor turnover in biotechnology is based on acquisition data from Thomson Reuters Recap.[5] and Evaluate[6] These databases provide a comprehensive record of significant acquisition and merger events in the biotechnology industry. Several deal types, i.e., mergers, takeovers, or acquisitions are listed, but we focus on acquisitions, where an acquirer firm obtains a controlling interest in the acquired firm. Acquisition events are critical as they represent organizational changes that can impact employee retention and innovation output.

Fig. 2 shows the evolution of these acquisitions over time and highlights an increase from a few acquisitions in 1990 to a peak of around 250 in 2007. There are overlaps in the transactions listed in RECAP and Evaluate. To ensure accuracy and eliminate redundancies, we merged acquisitions across the two datasets by matching the names of the two firms involved and the transaction year.

Our analysis focuses on a specific subset of these transactions. A prerequisite for inclusion in our dataset was that the acquired company had filed at least one patent application five years before the acquisition and that it had done so both before and after the event. This was necessary to identify inventors who worked for the acquired company and to ensure that it continued its R&D activities after the acquisition. After filtering based on these criteria, we identified 1,375 acquisitions.

To construct our counterfactual, we include only firms that have been acquired rather than firms that have not experienced such events. Specifically, we apply a staggered difference-in-differences approach to compare companies that have already been acquired (treated) with those that are likely to be acquired in the future (not yet treated). A not-yet treated firm is one that has not been acquired by the observation year but is acquired at a later date within the sample period. This methodology, inspired by Kim (2022), has recently been used to analyze the impact of acquisitions on employee entrepreneurship. Specifically, in this framework, time-specific treatment effects are computed for each firm and period, capturing the differential impact of acquisition across time (details are discussed in Section 4).

The rationale for this approach is based on the premise that firms involved in acquisitions may have particular characteristics compared to those not acquired, such as financial distress or the value of their intellectual property. By focusing on firms that are eventually acquired, we ensure that the control group is comparable to the treated firms, minimizing selection bias. Therefore, our analysis also includes companies that were not acquired during our observation period but could potentially be acquired in the future.

We assess the impact of acquisitions by comparing the outcomes of inventors from these 'not yet acquired' companies with those of inventors from acquired companies, enabling us to isolate the effect of acquisition events on key inventor-level outcomes.

For patent details, we rely on the disambiguated patent dataset from Morrison, Riccaboni, and Pammolli (2017), which provides a comprehensive set of patents filed with the USPTO, EPO, and PCT, covering patents in the US, Europe, and Japan. We rely on Google Patents for updated citation data through 2022.

To identify the inventors of the acquired companies, we collect patents filed by these companies within five years before the acquisition and list the inventors therein. The inventors' names have been disambiguated using established algorithms to account for variations in name spelling and ensure unique identification (Morrison et al., 2017). This allows us to track the inventors' patent activities both with the company and individually, giving us a comprehensive picture of their patenting behavior and the firms they worked for. We identified 15,318 inventors, with an average of 11.1 inventors working for an acquired company (see Fig. 3).

Our analysis employs a staggered difference-in-differences approach to assess the impact of acquisitions on inventor outcomes, focusing on inventor retention, patenting activity, and citation-weighted patenting. At the core of this analysis is the *Deal Year* marking the timing of each acquisition.

[5] Now Cortellis Deals Intelligence, http://recap.com/

[6] https://www.evaluate.com/

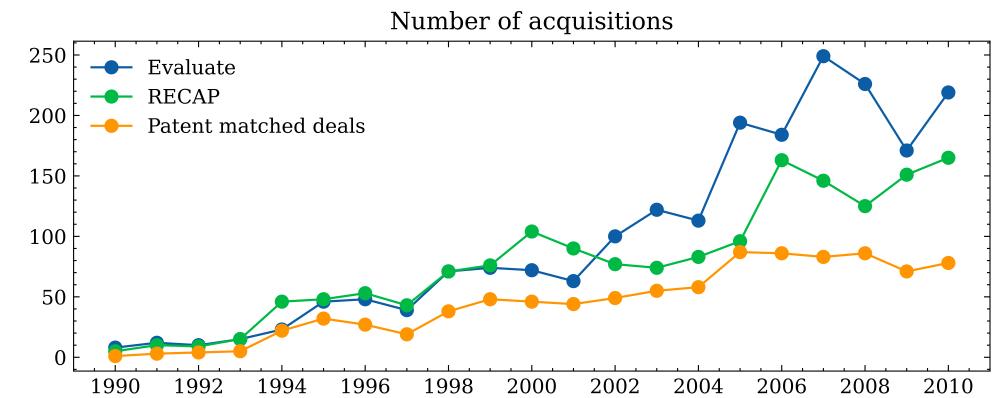

Fig. 2. Number of acquisitions in the biotech industry as recorded in RECAP and EVALUATE. These datasets were merged based on the names of the companies involved and the year of the acquisition. The inclusion criteria for the analysis were that the acquired company had filed at least one patent before the acquisition and that the acquirer had filed at least one patent before and after the acquisition. The orange curve labeled “Patent Matched Deals” shows the subset of deals that met these criteria and were included in our study.

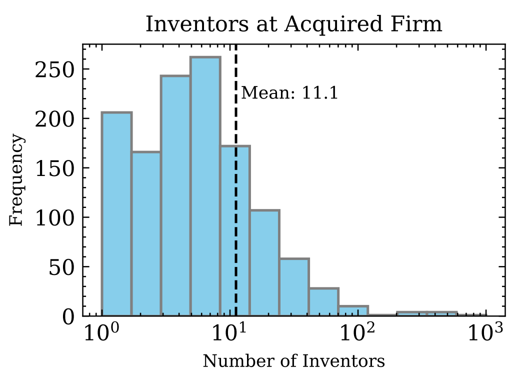

Fig. 3. Histogram of unique inventors filing patents for the acquired company five years before the event. These correspond to the inventors used in the main analysis.

We focus on four key outcomes: *Left*, *R&D Activity*, *Patents*, and *Citations*. The first two binary variables measure the impact of the acquisition on employee retention and inventors' ongoing R&D activity. *Left* indicates whether the inventor has filed any patent applications after this year either for the acquiring no the acquired form. Formally, for inventor i and year t, $\text{Left}_{i,t} = 1$ if t (or earlier) is the last year inventor i files a patent for either the acquiring or the acquired firm. Once $\text{Left}_{i,t} = 1$, the inventor never reappears in subsequent years' patent records for the newly integrated entity. If the inventor continues patenting within the combined firm, $\text{Left}_{i,t} = 0$. This variable thus captures the year an inventor ‘exits’ the post-acquisition organization, whether voluntarily or involuntarily. *No Longer Active* indicates inventors who filed their last patent the previous year.

We measure inventor retention using the variable Left, a binary indicator of whether an inventor ceases to file patents for the acquiring or acquired firm following the acquisition. This approach is consistent with Kapoor and Lim (2007) and Verginer, Parisi, van Lidth de Jeude, and Riccaboni (2025), who track inventor mobility through patent data.

We measure annual patent output and the citation-weighted impact of these patents to capture ongoing R&D productivity. This operationalization aligns with Ornaghi (2009), who evaluates post-acquisition patenting behavior in the pharmaceutical sector, and Hussinger (2010), who emphasizes the role of forward citations as a proxy for innovation quality. *Patents* and *Citations* measure productivity annually. *Patents* counts the number of patents the inventor has filed in a given year, and *Citations* reflects the number of citations these patents have received until 2022. We consider 12 years sufficient to assess the impact of the latest patents in our dataset (2010).

We consider several individual characteristics, including *Age*, *Tenure*, *Exclusivity*, and *Common IPC*. All variables are listed in Table 1.

Age is the number of years since the inventor's first patent filing, indicating their experience up to the acquisition point. *Tenure* measures the number of years since the inventor's first patent for the acquired firm. *Exclusivity* is a central metric assessing the inventor's focus on the acquired firm. It is calculated as the ratio of patents filed for the acquired firm to their total patents in the five years preceding the acquisition. Lastly, *Common IPC* quantifies the technological alignment between the inventor and the acquiring firm. It is computed as the number of International Patent Classification (IPC) classes shared between the inventor's patents and those of the acquiring firm on patents before the acquisition. This overlap indicates the technological synergy between the inventor's expertise and the acquiring firm's existing technological profile. Detailed descriptive statistics and alternative specifications regarding the technological distance between the inventor and the acquiring company are provided in the Supplementary Information Fig. 5.

Tables 2 and 3 descriptive statistics and the correlation table for the variables we use in our analysis.

4. Methodology

4.1. Difference-in-difference with multiple time periods

To assess the treatment effect of acquisitions on inventor retention, continued patenting, and patent output, we employ the generalized Difference-in-Differences (DiD) framework introduced by Callaway and Sant'Anna (2021b), Rios-Avila, Sant'Anna, and Naqvi (2022). This approach extends the common two-period DiD setting by allowing for staggered treatment timing and treatment effects across multiple time periods. Rather than imposing a single common treatment date for all firms, the method accommodates variation in when each firm is acquired, comparing those already treated to those that will be treated in the future (but have not yet been).

This staggered design enhances comparability: control units are more similar to the treated units in terms of their eventual likelihood of acquisition, thereby improving the plausibility of the parallel trends assumption. By leveraging the approach of Callaway and Sant'Anna (2021b), Rios-Avila et al. (2022) we can model treatment effects that vary by cohort and time.

Formally, our baseline event-study specification takes the following form:

$$Y_{it} = \sum_{\tau=-5}^{T=5} \lambda_\tau \text{After}_{it\tau} + \alpha_i + \xi_{ct} + \epsilon_i \tag{1}$$

Table 1
Detailed summary of the variables used in the analysis.

Variable	Description
Deal Year_i	Year in which the takeover was announced.
After_{it}	Dummy variable: 1 if the t is after the deal year, 0 otherwise.
Left_{it}	Dummy variable: 1 if the last year i filed a patent for either the acquiring or acquired company was before t, 0 otherwise.
Patents_{it}	Number of patents filed by inventor i in year t.
Citations_{it}	Citations received by 2022 for patents filed by inventor i in year t.
Age_i	Professional age at the time of acquisition, measured as the number of years since the first patent application.
Tenure_i	Years from the inventor's first patent filing for the acquired company to the year of acquisition.
Exclusivity_i	Proportion of patents filed by the inventor for the acquired company in relation to her/his total patents in the five years prior to the acquisition.
Common IPC_i	Number of shared International Patent Classification (IPC) subclasses between the inventor's patents and those of the acquiring firm before the acquisition. In our analysis, we use this variable in two forms: continuous measure and discretized variable categorized into three levels: 0, 1-3, and 4 or more.
R&D Activity_{it}	File at least on patent on or after year t.

Table 2
Descritpives statistics for main variables.

Variable	Mean	SD	Median	Min	Max	N
Patents	2.69	11.91	1	1	3 926	15 318
Citations	223.78	1 462.45	7	0	77 875	15 318
Age	8.40	7.34	6	2	65	15 318
Tenure	5.32	2.31	4	2	23	15 318
Common IPC	3.24	2.93	3	0	38	15 318
Exclusivity	0.44	0.45	0.29	0	1	15 318
Deal Year	2002.3	5.05	2003	1990	2010	15 318

Table 3
Correlations of main variables.

	Common IPC	Citations	Patents	Exclusivity	Tenure	Age
Common IPC	1					
Citations	0.064	1				
Patents	0.076	0.121	1			
Exclusivity	0.024	−0.040	−0.018	1		
Tenure	0.127	−0.015	0.003	0.248	1	
Age	0.018	0.025	0.031	0.002	0.296	1

where Y_{it} is the inventor-level outcome (such as continued patenting or citation-weighted output) for inventor i at time t. The binary indicator $\text{After}_{it\tau}$ equals one if the inventor's firm underwent an acquisition exactly τ years before or after year t, and zero otherwise. The analysis spans five years before ($\tau = -5$) and five years after ($T = 5$) the acquisition event. Individual fixed effects (α_i) control for time-invariant inventor characteristics, and company-by-year fixed effects (ξ_{ct}) absorb unobserved shocks common to all inventors within a firm and year. The error term (ϵ_i) captures any remaining idiosyncratic variation.

The analysis is conducted using the `did` R package (Callaway & Sant'Anna, 2021a), which implements the generalized DiD estimators from Callaway and Sant'Anna (2021b). Results are presented in Fig. 4, showing the Average Treatment Effects on the Treated (ATT) for different treatment cohorts and time horizons, and Table 4 reports the overall ATT.

4.2. Aggregate interaction design

To streamline the analysis and estimate the average effect over five years after the event, we change Eq. (1) by estimating a single 'After' parameter, λ, instead of the previous 11 different λ_τ parameters. This simplification helps tackle the model's complexity, especially when additional interaction effects are included. The revised model is:

$$Y_{it} = \lambda \text{After}_{it} + \alpha_i + \xi_{ct} + \epsilon_i \tag{2}$$

Extending this model, we introduce interaction terms to assess the impact of factors such as inventor exit, age, exclusivity, and technological overlap. To examine the impact on patenting activity post-departure, we use:

$$Y_{it} = \lambda \text{After}_{ict} + \beta_1 \text{Left}_i + \beta_2 \text{After}_{it} \times \text{Left}_i + \xi_{ct} + \epsilon_i \tag{3}$$

We omit individual fixed effects to avoid collinearity with fixed inventor characteristics, while still retaining firm and time fixed effects. Here, β_2 represents the net effect of 'Left' after acquisition on the outcome Y_{it}.

By integrating interactions with other variables, we can further disaggregate the nuances of the takeover, focusing on the *left* status:

$$\begin{aligned} Y_{ict} = {} & \lambda \text{After}_{ict} + \beta_1 \text{Left}_i + \beta_2 \text{After}_{ict} \times \text{Left}_i \\ & + \beta_3 \text{Exclusivity}_i + \beta_4 \text{Exclusivity}_i \times \text{After}_{ict} \\ & + \beta_5 \text{Exclusivity}_i \times \text{Left}_i + \beta_6 \text{Exclusivity}_i \times \text{Left}_i \times \text{After}_{ict} \\ & + \beta_7 \log(\text{Age}_i) + \beta_8 \log(\text{Tenure}_i) + \beta_9 \text{Common IPCs}_i \\ & + \xi_{ct} + \epsilon_i. \end{aligned} \tag{4}$$

To understand the impact of exclusivity on inventors' post-acquisition productivity, we mainly focus on β_6, which captures the net effect of post-acquisition exit through the level of exclusivity.

To investigate the influence of age, we replace *Exclusivity* in Eq. (4) with *Log (Age)*.

To assess technological similarity, we categorize Common IPCs_i into three levels: 0, 1-3, and 4 or more. By discretizing Common IPCs_i and including these levels in our model, we can identify potential non-linear effects.

One alternative found in the literature is a matched Difference-in-Differences (in a two-by-two design) approach, which compares treated inventors before and after acquisitions to similar, never-treated inventors from companies that never experienced an acquisition (Verginer et al., 2025). This two-level matching procedure first identifies comparable non-acquired firms and then, within that matched set, pairs inventors from acquired firms with inventors from the non-acquired firms. Although this approach can enhance comparability, it comes at the cost of significantly reducing the sample—from over a thousand acquisitions to fewer than fifty—due to its stringent matching requirements. Moreover, it may still be vulnerable to unobservable differences between the matched, never-acquired firms and the acquired firms, potentially compromising the validity of the counterfactual. For these reasons, we rely on the not-yet-treated inventors within firms that will be acquired in the future as our comparison group.

A further methodological concern is the continued observability of inventors. Since our data track inventors through their patent filings, those who cease patenting effectively disappear. If the likelihood of continued patenting changes following a move to a new employer,

Table 4
Average Treatment Effect on the Treated (ATT) after the acquisition.

	ATT	Std. Error	95% Conf. Int.
Left	0.135	0.016	(0.10, 0.17)
R&D Activity	−0.063	0.009	(−0.08, −0.05)
log (patents)	−0.136	0.027	(−0.19, −0.08)
Log (citations)	−0.350	0.070	(−0.49, −0.21)

Control Group: Not Yet Treated; Estimation Method: Doubly Robust.

observed productivity could be biased. However, Verginer et al. (2025) using a Heckman selection model, find that the probability of inventor exit remains constant, suggesting that "going dark" (ceasing to file patents) does not bias productivity comparisons among active inventors. This supports our focus on the moderating effect of inventor characteristics on active inventors' productivity before and after takeovers, while maintaining the not-yet-treated comparison framework.

5. Results

5.1. The impact of acquisitions on inventor retention and r&d productivity

Takeovers of high-tech companies are notoriously disruptive events, especially in terms of the turnover of inventors and other highly skilled workers, as noted by Fernandez De Arroyabe Arranz and Hussinger (2018). However, the impact of these takeovers goes far beyond the mere attrition rate.

Kapoor and Lim (2007) found that acquisitions negatively affect the patent production of inventors working for semiconductor companies. More recently, Kim (2022) has shown that acquisitions significantly increase the rate of inventor entrepreneurship. These studies illustrate the different consequences of takeovers in high-tech sectors.

In our analysis, we take a broader perspective to examine the causal effects of acquisitions on the mobility and productivity of inventors who worked at the target firm before the acquisition. We consider the impact of acquisitions in four dimensions: (i) the turnover of inventors from acquired firms; (ii) the R&D productivity of inventors from acquired firms, measured by the number of patents filed; (iii) the citation-weighted number of patents of inventors from the target company as an alternative measure of R&D productivity; and (iv) the probability that inventors will no longer apply for patents after the acquisition.

We use a staggered difference-in-differences approach to quantify these effects, which is explained in more detail in the Methods section. The results in Table 4 refer to the biotech sector between 1990 and 2010. We find that acquisitions significantly disrupt innovation in all four dimensions.

Specifically, the turnover of the acquired company's inventors increases by 13.5After takeovers, we also found a significant increase in the number of inventors who no longer apply for patents (+6.3%). In terms of R&D productivity, takeovers lead to a significant decrease in the number of patents filed (−13.6%). If we look at the number of patents weighted by citations, the decline is even more pronounced (−35%).

Fig. 4 shows the effects of takeovers over the five years following the event. Since takeovers are not random events, the effects in the pre-acquisition phase could be anticipated to a certain extent. In Fig. 4, however, we find no pre-trend for all dependent variables of interest.[7] In general, we find negative effects that become significant in the two years following the acquisition. The effects persist five years after the acquisition, with R&D productivity tending to level off after three years.

Using the staggered difference-in-differences analysis outlined in the Methods section, our study shows that acquisitions significantly affect acquired inventors. We find inventors are significantly more likely to leave after an acquisition, suggesting that such corporate reorganizations create an environment of uncertainty. This increase in departures can also be attributed to personnel changes, such as layoffs or terminations, that occur during post-acquisition phases.

The analysis goes beyond retention to highlight the impact on the survival of inventors in the industry following an acquisition. This aspect of our findings highlights the broader impact of acquisitions, not only on immediate employment status but also on long-term career trajectories.

In terms of productivity, our results suggest that the number of patents filed and their impact, as measured by the number of citations, declined after the acquisition. This reduction in innovation performance is concerning as it indicates a potential loss of innovation capacity following biotech takeovers. Such a trend could be due to various factors, e.g., a change in corporate strategy, a change in workplace culture, a restructuring of R&D, or a reallocation of resources away from research and development activities.

These collective findings paint a picture of the acquisition event as a significant disruptive factor for inventors, which not only accelerates their departure—whether voluntary or not—but also has a detrimental effect on their innovation and productivity. This observation raises important questions about the mechanisms that drive these patterns and how they can be mitigated to preserve human capital during corporate transitions.

In short, we find strong support for H1 that acquisitions negatively affect inventors' productivity with no clear signs of recovery in the five years following these events.

It is important to point out that our analysis is based on the assumption of common trends, validated by visual inspection and statistical tests using the "did" package in R (Callaway & Sant'Anna, 2021a). This validation strengthens the interpretations and conclusions we draw from our study.[8]

5.2. Stay or leave: the moderating effects of experience, specificity and similarity

To address H2, H3, and H4, which examine the impact of acquisitions on inventors' productivity as a function of whether they stayed in or left the firm, we estimate an aggregate after-effect as described in the Methods section, focusing on the total effect after the event.

Again, the overall effect in Table 5 shows a general decline in productivity after the takeover, as seen from the lower number of patents filed and the citations these patents received in the following years. Notably, despite the general decline in productivity, the inventors who left the company before or after the takeover were more productive than those who stayed.

After controlling for tenure, age, exclusivity, and common IPCs, we find that these factors also moderate productivity levels. To better understand how these factors influence productivity as a function of the inventor's decision to stay or leave, we introduce an interaction term into the base model described in the Methods Section.

In Table 6, we investigate how age affects productivity after an acquisition, depending on whether the inventors stay in or leave the company. Our results suggest that experienced inventors are more likely to stay with the company after the acquisition. Experienced inventors who leave the company tend to experience a significant drop in productivity compared to their colleagues who stay with the company. This suggests that experienced inventors are more productive

[7] To test the parallel trends assumption, we use the R `did` package (Callaway & Sant'Anna, 2021b), also employed in the main analysis, which reports a p-value of 0.35, providing no evidence of pre-trends.

[8] For an alternative matched diff-in-diff approach, see Verginer et al. (2025). The results are consistent, but a much smaller set of acquisition events is considered.

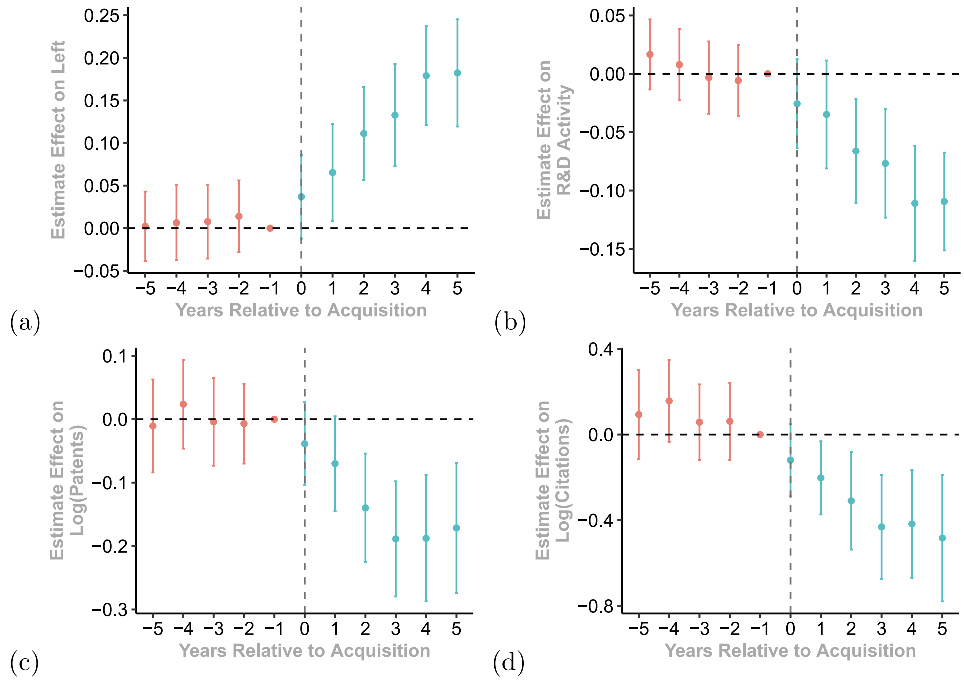

Fig. 4. Average Treatment Effect on the Treated (ATT) before and after acquisitions. These figures show the estimated λ_τ from Eq. (1) together with the 95% confidence interval. The year $t-1$ is the reference point. (a) examines the impact on inventor turnover. (b) looks at the probability that the inventor no longer applies for patents. (c) and (d) show the change in inventor productivity as measured by the number of patents and citations.

Table 5
Regression results, leave versus stay.

	(1) Left	(2) log (Patents)	(3) log (Citations)	(4) Left	(5) log (Patents)	(6) log (Citations)
After	0.142*	−0.109*	−0.319*	0.115*	−0.126*	−0.351*
	(35.13)	(−12.28)	(−13.60)	(29.77)	(−14.53)	(−15.25)
Left		−0.324*	−0.844*		−0.344*	−0.879*
		(−42.91)	(−41.31)		(−44.61)	(−41.85)
Left × After		0.059*	0.219*		0.056*	0.214*
		(5.44)	(7.68)		(5.28)	(7.59)
log (Tenure)				0.178*	0.081*	0.251*
				(70.45)	(13.22)	(15.64)
Exclusivity				−0.222*	−0.084*	−0.149*
				(−82.18)	(−14.96)	(−9.83)
log (Age)				0.065*	0.010	−0.051*
				(32.75)	(2.01)	(−3.79)
Common IPCs				−0.008*	0.070*	0.161*
				(−19.87)	(74.97)	(71.36)
Constant	0.228*	0.972*	2.638*	−0.120*	0.590*	1.776*
	(149.01)	(270.83)	(277.48)	(−29.06)	(63.25)	(72.25)
Acquiring Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Acquired Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144 532	144 532	144 532	144 532	144 532	144 532
R^2	0.32	0.11	0.21	0.40	0.15	0.24
AIC	120,592	345,942	630,043	102,645	338,108	624,297
Log Lik.	−60,294	−172,967	−315,017	−51,317	−169,046	−312,140

t statistics in parentheses; † $p < 0.01$, * $p < 0.001$.

if they remain in the company after the acquisition, which is consistent with H2. The acquiring company can better assess the value of experienced inventors whose record track of R&D productivity is more informative. The innovation potential of young acquired inventors is more uncertain. Therefore, they are more likely to leave the company after the acquisition and be more productive when they leave.

Shifting our focus to exclusivity – a measure that reflects an inventor's external collaborations and their focus on firm-specific technologies – we see some interesting patterns in Table 7. Inventors with higher exclusivity, i.e., those who primarily apply for patents only for the acquired company, are initially less likely to leave the company, and this does not change after the event, although the effect becomes less significant.

In terms of productivity, there is a significant drop in productivity for those with higher exclusivity, both in terms of the number of patents and the citation-weighted patent production after the event. However, the productivity of those who leave the company after the event is higher than that of the similarly exclusive inventors who

Table 6
Regression results for inventor experience (Age).

	(1) Left		(2) log (Patents)		(3) log (Citations)	
After	0.205*	(29.14)	−0.243*	(−13.06)	−0.736*	(−15.08)
log (Age)	0.083*	(40.78)	−0.032*	(−5.45)	−0.196*	(−12.56)
After × log (Age)	−0.046*	(−13.91)	0.060*	(6.43)	0.198*	(8.52)
Left			−0.896*	(−25.47)	−2.464*	(−25.89)
Left × After			0.516*	(12.35)	1.385*	(12.39)
Left × log (Age)			0.220*	(16.00)	0.637*	(17.57)
Left × After × log (Age)			−0.177*	(−10.10)	−0.442*	(−9.73)
Exclusivity	−0.219*	(−81.68)	−0.071*	(−12.38)	−0.110*	(−7.17)
Common IPCs	−0.008*	(−19.63)	0.070*	(75.19)	0.162*	(71.70)
log (Tenure)	0.179*	(70.73)	0.070*	(11.35)	0.216*	(13.43)
Constant	−0.163*	(−38.84)	0.694*	(61.01)	2.131*	(69.07)
Acquiring Firm FE	Yes		Yes		Yes	
Acquired Firm FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Observations	144 532		144 532		144 532	
R^2	0.40		0.16		0.24	
AIC	102,414		337,782		623,822	
Log Lik.	−51,200		−168,880		−311,900	

t statistics in parentheses; † $p < 0.01$, * $p < 0.001$.

Table 7
Regression results for knowledge specificity (Exclusivity).

	(1) Left		(2) log (Patents)		(3) log (Citations)	
After	0.122*	(28.76)	−0.107*	(−10.25)	−0.282*	(−10.28)
Exclusivity	−0.217*	(−77.99)	−0.030*	(−4.28)	0.018	(0.94)
After × Exclusivity	−0.017†	(−3.26)	−0.064*	(−4.59)	−0.218*	(−6.16)
Left			−0.245*	(−24.72)	−0.584*	(−22.06)
Left × After			−0.039†	(−2.78)	−0.082	(−2.22)
Left × Exclusivity			−0.317*	(−18.41)	−0.940*	(−19.52)
Left × After × Exclusivity			0.300*	(12.40)	0.918*	(14.16)
Common IPCs	−0.008*	(−19.85)	0.070*	(74.99)	0.161*	(71.39)
log (Tenure)	0.178*	(70.82)	0.067*	(10.84)	0.211*	(13.02)
log (Age)	0.066*	(32.92)	0.014†	(2.78)	−0.039†	(−2.84)
Constant	−0.124*	(−30.53)	0.583*	(60.33)	1.750*	(68.29)
Acquiring Firm FE	Yes		Yes		Yes	
Acquired Firm FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Observations	144 532		144 532		144 532	
R^2	0.40		0.16		0.24	
AIC	102,633		337,834		623,957	
Log Lik.	−51,310		−168,906		−311,968	

t statistics in parentheses; † $p < 0.01$, * $p < 0.001$.

stay. These observations suggest that acquiring firms retain inventors closely associated with the target company. However, on average, these inventors become more productive when they move to a third party. In line with H3, it is more challenging to correctly evaluate innovations specific to the target company. Difficulty in absorbing target firm-specific knowledge is one of the main causes of the decline in productivity in R&D following takeovers.

This observation prompts us to examine the role of technological overlap in shaping productivity outcomes more closely. Concerning H4, we examine whether the extent of technological fit between an inventor and the acquiring firm affects productivity and the likelihood of retention. Our analysis focuses on the impact of common International Patent Classification (IPC) subgroup classes between the inventor and the acquiring firm on these metrics.

Table 8 shows how technological overlap, as measured by common International Patent Classification (IPC) subgroup classes, affects inventors' retention and productivity after acquisition. The results indicate that inventors with a significant overlap (4 or more common IPC classes) with the acquiring company are less likely to exit after the acquisition. In contrast, inventors without a common IPC are significantly more likely to leave. This trend supports the idea that acquiring companies retain inventors whose expertise is better aligned with their ongoing R&D activities.[9]

The analysis also shows that post-acquisition, inventors with the highest degree of technological overlap (4 or more IPC classes) experience the most significant increase in productivity, while those with no or partial (0 and 1-3 IPCs in common) experience a drop in productivity, regardless of whether they stayed or not.

To summarize, inventors with strong technological ties to the acquiring company are less likely to leave, and inventors without technological overlaps suffer a more significant decline in productivity if they stay with the acquiring company. Inventors whose expertise closely matches the acquiring company's current R&D focus tend to stay and experience increased productivity. Conversely, inventors with little or no overlap in technological areas find it challenging to find a good fit inside and outside the acquiring company. Taken together,

[9] Similar results are obtained when focusing on the most important acquisitions and use a matched diff-in-diff regression strategy (Verginer et al., 2025). A breakdown with five levels of similarity, showing qualitatively identical results, is available in the appendix in Table 2.

Table 8
Regression results for knowledge similarity (IPC Overlap).

	(1) Left		(2) log (Patents)		(3) log (Citations)	
Before × 0 IPC	0.000					
Before × 1-3 IPC	−0.111*	(−22.38)				
Before × 4+ IPC	−0.150*	(−28.34)				
After × 0 IPC	0.126*	(15.57)				
After × 1-3 IPC	−0.003	(−0.39)				
After × 4+ IPC	−0.030*	(−4.45)				
Stayed × Before × 0 IPC			0.000	(.)	0.000	(.)
Stayed × Before × 1-3 IPC			0.096*	(8.78)	0.182*	(5.73)
Stayed × Before × 4+ IPC			0.459*	(38.52)	1.042*	(30.84)
Stayed × After × 0 IPC			−0.092*	(−4.08)	−0.294*	(−5.02)
Stayed × After × 1-3 IPC			0.025	(1.71)	−0.038	(−0.94)
Stayed × After × 4+ IPC			0.280*	(18.20)	0.578*	(13.82)
Left × Before × 0 IPC			−0.359*	(−23.13)	−0.989*	(−22.52)
Left × Before × 1-3 IPC			−0.291*	(−21.23)	−0.815*	(−20.81)
Left × Before × 4+ IPC			0.176*	(10.15)	0.384*	(8.23)
Left × After × 0 IPC			−0.310*	(−16.47)	−0.707*	(−13.17)
Left × After × 1-3 IPC			−0.288*	(−19.27)	−0.836*	(−19.80)
Left × After × 4+ IPC			−0.012	(−0.73)	−0.044	(−1.01)
Exclusivity	−0.218*	(−80.57)	−0.080*	(−13.97)	−0.138*	(−9.05)
log (Tenure)	0.174*	(68.74)	0.080*	(12.90)	0.252*	(15.49)
log (Age)	0.065*	(32.49)	0.030*	(5.73)	−0.011	(−0.79)
Constant	−0.026*	(−4.23)	0.567*	(42.42)	1.755*	(46.84)
Acquiring Firm FE	Yes		Yes		Yes	
Acquired Firm FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Observations	144 532		144 532		144 532	
R^2	0.40		0.14		0.23	
AIC	102,003		340,888		625,939	
Log Lik.	−50,992		−170,429		−312,954	

t statistics in parentheses; † $p < 0.01$, * $p < 0.001$.

these results support Hypothesis 4, that technological overlaps facilitate the absorption of the target company's knowledge. Therefore, the disruption of R&D productivity is much stronger for acquired inventors without technological overlaps.

The combined effects of age, exclusivity, and technological similarity on inventor productivity post-acquisition reveal the complex interplay of talent retention and innovation. Older inventors, with their experience and established expertise, tend to stay with the acquiring firm and maintain their productivity. In contrast, exclusive inventors, despite their specialized knowledge of the acquired firm's technology, may struggle to assimilate into the new environment and, therefore, become more productive elsewhere. In addition, inventors with a technological overlap above the median are more likely to remain in the acquiring firm and experience higher R&D productivity. This suggests that a low or no technological match could lead to underutilizing their skills in the new organizational environment. Overall, the decline in inventor productivity following biotech acquisitions is driven by fundamental uncertainty and disagreement in assessing the potential value of young and exclusive inventors. Even among inventors working in different technology areas, there is a significant decline in productivity following acquisitions.

6. Conclusion

Acquiring firms is a strategic approach to accessing external knowledge in sectors characterized by rapid technological advancements and complex knowledge bases, such as the biotechnology industry (Carayannopoulos & Auster, 2010). Nevertheless, integrating new knowledge often requires reorganizing R&D activities within the merged entities (Capron, Mitchell, & Swaminathan, 2001; Colombo & Rabbiosi, 2014; Karim & Mitchell, 2000). These reorganizations can create uncertainty and conflict, prompting the departure of creative talent and significantly undermining the anticipated advantages of the acquisition (Arroyabe, Hussinger, & Hagedoorn, 2020; Ernst & Vitt, 2000; Fernandez De Arroyabe Arranz & Hussinger, 2018; Kapoor & Lim, 2007; Kim, 2022; Paruchuri, Nerkar, & Hambrick, 2006).

As highlighted by Colombo and Rabbiosi (2014), investigating how acquisitions affect R&D performance and inventor turnover is complicated by causal ambiguity and the difficulty of observing outcomes at the individual inventor level over extended periods (Kapoor & Lim, 2007). To address this gap, we employ a generalized difference-in-differences approach and leverage a newly compiled dataset that disambiguates inventors and assignees (Morrison et al., 2017). Focusing on the biotech takeover wave at the turn of the century, we document a significant and persistent disruption in R&D productivity: inventors are more likely to leave (+13.5%) or become inactive (+6.3%) following takeovers, and average patent production declines markedly (−13.6% in patents, −35% in citation-weighted patents). These magnitudes are consistent with prior evidence (Carriquiry, 2018; Ernst & Vitt, 2000; Ranft & Lord, 2000) and underscore the depth of the disruption. Surprisingly, we find that inventors who leave after an acquisition are more productive and receive more citations than those who stay.

The study shows that these adverse effects are not uniform: they are less pronounced for experienced inventors and those whose technological profile overlaps with that of the acquiring company. At the same time, they are more pronounced for younger inventors and those with a more specialized technological profile. These results highlight that M&As can jeopardize target-specific human capital, with heterogeneous effects on the integration of human capital for innovation after an acquisition.

Turnover spikes immediately after the acquisition, as expected, but paradoxically, it is often the most valuable inventors—those whose knowledge may have motivated the acquisition—who depart first. Their exodus reduces productivity among the remaining inventors, an unexpected consequence that exposes the fragility of post-acquisition integration. Young inventors, whose long-term potential is difficult to gauge, struggle to adapt and often fare better after leaving. Similarly, inventors whose expertise is closely tied to the target company's technologies find it challenging to integrate and become more productive outside the acquiring firm. In contrast, those who have worked exclusively for the target company are more likely to stay, but again, the remaining exclusive inventors are less productive than similar inventors who leave after the acquisition. These patterns suggest that while acquisitions aim to harness external knowledge, they may inadvertently erode the tacit, experience-based competencies that underpin innovative capacity.

Theoretical implications. Our findings advance the theoretical understanding of post-merger integration by showing how acquisitions can inadvertently undermine a firm's innovative capacity—a result that resonates with the knowledge-based view of the firm (Grant, 1996). This perspective emphasizes that competitive advantage arises not only from acquiring codified intellectual property but also from integrating and sustaining tacit, context-specific knowledge held by individuals. Our inventor-level analysis reveals how uncertainty and mismatches between inventors' expertise and the acquiring firm's R&D portfolio may impede the smooth integration of knowledge. Far from being a straightforward process of absorbing external know-how, acquisitions often unsettle the delicate ecosystem that allows tacit knowledge to thrive, ultimately limiting the expected gains in innovation.

Managerial implications. From a managerial standpoint, these findings suggest that successful acquisitions require more than a strategic evaluation of formal IP assets. Managers must also anticipate the human and organizational challenges that arise when merging distinct R&D environments. Retaining and motivating key inventors—particularly those who are young, specialized, or highly valued—demands targeted integration strategies. Maintaining existing research teams where possible, providing pathways for professional growth, and fostering environments that encourage trust and collaboration can mitigate the disruptive effects of uncertainty. Identifying inventors experienced in working with multiple firms may help post-acquisition integration, as they may be better equipped to navigate organizational change.

Ultimately, managers who fully appreciate the complexity of tacit knowledge integration stand a better chance of realizing the acquisition's innovative potential. By analyzing the heterogeneous effects of M&As on inventors' productivity at the individual level, our work contributes to better predicting which inventors are likely to remain with the firm after the acquisition and continue contributing to its R&D productivity. This opens the possibility of more accurately assessing the potential impact of an acquisition and better targeting efforts to retain the most talented inventors—those most at risk of leaving.

Future research directions. This study opens several avenues for future research. First, examining team-level dynamics could deepen our understanding of how post-acquisition R&D reorganization affects the retention and transmission of tacit knowledge. Second, the use of matched employer-employee datasets (Arnold et al., 2023) may help distinguish between voluntary and involuntary inventor departures, clarifying whether organizational restructuring or personal dissatisfaction drives attrition. Third, applying the analytical framework to other high-innovation industries could test the generalizability of our findings across different technological and competitive environments. Fourth, inventor-level matching techniques could be explored to further account for heterogeneity and refine causal estimates. Finally, investigating inventors' long-term career trajectories—and their impact on the broader innovation ecosystem—could inform both academic debate and practical policy design. In particular, regulators might consider how to address "killer acquisitions" (Cunningham et al., 2021) that deliberately limit innovation.

In sum, our study illustrates that acquisitions, while strategically deployed to absorb external knowledge, can have unintended consequences for R&D personnel and innovation. By highlighting the complexities of tacit knowledge integration and inventor turnover, we offer a more nuanced view of why acquisitions sometimes fail to deliver on their innovative promise.

CRediT authorship contribution statement

Luca Verginer: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Massimo Riccaboni:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization.

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The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbusres.2025.115573. The SI contains additional regressions and robustness checks.

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