The Human Capital Reallocation of M&As: Inventor-level Evidence

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Abstract

Mergers and acquisitions (M&As) of innovative firms lead to significant inventor restructuring, with high turnover among target inventors. Following M&As, both retained and departing inventors show increased patenting performance. Acquirers retain productive inventors whose expertise aligns with the merging firms, while external hires bring knowledge from non-core areas. Productivity gains for inventors switching jobs are concentrated among non-top performers and those with higher technological overlap at their new employers. These findings suggest that M&As reduce labor market frictions for inventors, reallocating them to more valuable roles within and beyond the merging firms.

Keywords: Labor Restructuring, Human Capital, Innovation, Inventors, Mergers and Acquisitions, Labor Market Frictions

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1 Introduction

Mergers and acquisitions (M&As) reallocate resources, including both physical assets and human capital. Prior literature has documented extensive post-merger physical asset restructuring (Kaplan and Weisbach, 1992, Schoar, 2002, Maksimovic et al., 2011) and finds that mergers reallocate assets toward higher valued uses (Jovanovic and Rousseau, 2008). Such reallocation accounts for the majority of the gains from mergers (Devos et al., 2009). However, the literature on the impact of M&As on human capital reallocation is still nascent.[1] In this study, I analyze whether M&A transactions lead to an analogous reallocation of human capital across firms.

Given that human capital is a crucial factor in production, it is plausible that M&As also reallocate human capital toward higher valued uses. However, unlike physical assets, an acquiring firm has less control over employees relative to physical assets, who can leave the combined entity regardless of the acquirer's intentions. While employees can switch jobs without M&As, their mobility is constrained by labor market frictions, including search and relocation costs, employee inertia, and regulatory restrictions like non-compete agreements. Labor market frictions also manifest in the form of "implicit trust" within long-term contract between employees and firms, as posited by Shleifer and Summers (1988). Additionally, firms bear significant labor hiring costs, including search costs and training costs (Hamermesh, 1996, Bloom, 2009, Belo et al., 2014). These frictions collectively inhibit employees from being reallocated to their best valued uses.

Arguably, M&As can mitigate such frictions for employees both within and outside the merging firms. For employees within the merging firms, M&As may lower the marginal cost of job searching by decreasing employee inertia, whether through voluntary departures of employees who do not wish to stay in the combined entity or through involuntary layoffs. For external employees, M&As may reduce search costs by expanding the pool of job opportunities as a newly-combined entity forms. Nonetheless, it remains an empirical question (1) whether these frictions are significant in the first place and (2) to what extent M&As can mitigate them sufficiently to induce observable employee reallocation and changes in employees' productivity in the post-merger period. Furthermore, even if firms retain the desired employees, variation in corporate culture or

[1]Some notable recent exceptions include Ouimet and Zarutskie (2020), Lagaras (2021) and Gehrke et al. (2021), which are discussed later in the introduction, and this study complements this stream of research.

organizational structure may negatively impact their productivity (Li et al., 2021). Consequently, it is unclear whether post-merger human capital reallocation is economically important.

I address this issue by analyzing the reallocation of a specific type of human capital — i.e., inventors — both within and beyond merging firms around M&A deals. Specifically, this study provides evidence on three key questions: 1) What is the extent of inventor restructuring after M&As? 2) How does the innovation productivity of inventors change after M&As, both for those who remain with the combined entity and for those who leave? and 3) What are the possible economic forces driving such reallocation?

I focus on this subset of employees for several key reasons. As highly skilled employees, inventors make up an important intangible asset of a firm (Mailath and Postlewaite, 1990, Ouimet and Zarutskie, 2020) and are key inputs in the innovation process (Chen et al., 2016). Their contributions build firms' knowledge base, which generates revenues and ultimately adds to firm value in the future (Hall, 2002, Kogan et al., 2017). In addition, the inventor-level analysis is particularly well-suited for this context due to two key attributes. First, following established empirical approaches (Seru, 2014, Bernstein, 2015, Liu et al., 2023, Li and Wang, 2023), I construct a novel dataset that links inventors with their assignee firms to track each inventor's career trajectory throughout their active patenting career. This enables me to document both the subsequent employers of departed inventors and the former employers of inventors newly hired by the combined entity. Therefore, I can provide a comprehensive view of inventor restructuring across firms. Second, patent-based measures provide a useful metric for assessing each inventor's productivity in terms of both the quantity and quality of their innovative output.[2]

My sample covers 845 U.S. public M&A deals announced after Jan 1, 1984, and completed before Dec 31, 2017, in which both acquirer and target firms have at least one inventor one year prior to the deal announcement date. For the empirical analysis, I classify inventors involved in these M&As into three groups: (1) retained inventors, (2) departed inventors, and (3) newly

[2] Several recent papers also make use of the benefits of inventor-level data. For instance, Bernstein et al. (2021) investigates the impact of negative household wealth shocks during the financial crisis on inventor productivity. Similarly, Zhao (2021) explores how reduced asymmetric information following patent publication affects inventor mobility and productivity. Additionally, Bena et al. (2021) finds that post-merger, target inventors who remain with the combined entity patent more specifically to acquirer inventors, suggesting that inducing target firms to make specialized investments can be a motive for M&As.

hired inventors. Among the first two groups, I further classify inventors into those from acquirer firms (i.e., acquirer inventors) and those from target firms (i.e., target inventors). To construct a balanced control sample for the merging firms, I create a candidate pool of firms that have not been involved in any innovative mergers over a ten-year period. From this pool, I select up to two firms per acquirer (or target) that are in the same industry and have the closest propensity score. The propensity score is estimated using a standard set of variables known to influence merger involvement, measured one year before the deal announcement, as well as covariates reflecting the firms' pre-merger innovation activity. Then, I use a difference-in-differences (DiD) specification at the firm level to analyze inventor turnover around M&As.

I find substantial restructuring within the combined entity's inventor workforce, driven primarily by the higher departure rate of target inventors. This rate increases significantly by 5.6 to 5.9 percentage points relative to matched control firms in the post-merger period. In contrast, inventors at acquiring firms experience a modest yet statistically significant reduction in the departure rate, ranging from 1.4 to 2.3 percentage points. Additionally, the combined entity continues to recruit externally at the same rate as before the merger, and the total size of the inventor team remains relatively unchanged.

Then, I examine changes in inventors' productivity following M&As using a similar DiD specification at the inventor-level. The results show an overall improvement in productivity for inventors within the combined entity post-merger. Compared to inventors that remain with the matched acquirer firms, those in the combined entity file 4.5% more patents, 21% more citation-weighted patents, and generate 2.5% higher economic value from their patents. This effect is mainly driven by acquirer inventors who stay and newly hired external inventors. Moreover, departed inventors also show an increase in innovation productivity, filing 2.9% more patents and 7.5% more citation-weighted patents. These findings suggest that labor market frictions play a critical economic role for inventors, and that M&As reduce these frictions to some extent, reallocating inventors both within and beyond merging firms to roles where their talents are better utilized.

To understand the determinants of labor outcomes for inventors within the merging firms, I begin by analyzing how acquirers restructure inventors from both the target and their own firms.

I propose two non-mutually exclusive channels. The first is the *matching channel*, where acquirers may be ex-ante interested in a subset of target inventors patenting in the target firm's core business areas, or inventors from both merging firms whose patenting expertise aligns more directly with the acquirer's own core business. The second is the *screening channel*, where acquirers aim to retain inventors based on their ex-ante productivity and streamline operations by laying off lower-quality or redundant employees (Lee et al., 2018, Lagaras, 2021). To test these channels, I examine the cross-sectional post-merger labor outcomes of inventors in the merging firms.

The combined effect of the matching and screening channels provides a consistent explanation for post-merger labor outcomes among inventors in the merging firms. Acquirers are particularly effective at retaining highly productive inventors whose expertise closely aligns with the merging firms' core technological areas. Specifically, target inventors whose expertise matches the target's patenting areas, as well as inventors from either firm whose expertise overlaps with the acquirer's core areas, are less likely to leave if they are highly productive. On the other hand, the *matching channel* plays a more dominant role in explaining turnover. Inventors whose expertise is less aligned with their employer's core technological areas face significantly higher turnover. The *screening channel* — retaining productive inventors — seems less effective on its own, as highly productive inventors are sometimes more likely to leave post-merger.

Conversely, external hires after M&As bring productive expertise from non-core areas. This hiring strategy complements the internal restructuring, where highly productive inventors in peripheral technological areas are less likely to stay post-merger. Cross-sectional analysis shows that inventors are more likely to be new hires than retained inventors if they work in areas peripheral to the combined entity's core business, are more productive both overall and in peripheral fields, and tend to patent across multiple areas (i.e., generalists). Additionally, inventors with less experience, such as smaller networks and fewer active patenting years, are more likely to be new hires.[3] These findings support the idea that M&As reduce labor market frictions for external inventors by expanding their job opportunities. This reduction in frictions facilitates the entry of high-potential, younger talent into the combined entity, expanding the firm's innovation capacity.

[3]These findings align with Gehrke et al. (2021), who find that post-merger firms tend to hire younger but slightly higher-skilled external employees.

While much of the existing literature has focused on inventors who remain within the merging firms, those who leave or join the combined entity post-merger have received little attention. The finding that these inventors experience a significant boost in innovation productivity suggests that M&As not only reduce inefficiencies within firms but also extend benefits to inventors moving across them. Moreover, these groups provide an ideal context to examine how reduced labor market frictions drive productivity improvements. If reduced frictions are indeed the mechanism, we would expect inventors facing greater constraints before the merger to benefit more. My subsample analysis, which categorizes inventors by their pre-merger productivity, supports this hypothesis. I find that post-merger productivity increases are predominantly driven by non-top performers. Departed inventors in this group see a 5.1% increase in patent filings and a 22% rise in citation-weighted patents, while newly hired inventors with lower pre-merger performance experience a 20% growth in citation-weighted patents. In contrast, highly productive inventors, who typically face fewer labor market frictions, show no significant post-merger improvements.

I also examine employer-employee technological overlap as a potential mechanism for reducing these frictions. This overlap is calculated using the cosine similarity of technology classification vectors derived from patents filed by inventors and their post-merger employers, up to one year before the deal announcement. The heterogeneity analysis shows that post-merger productivity improvements among inventors moving across firms are primarily driven by those with greater technological overlap at their new employers. Departed inventors with higher overlap file 9.1% more patents and 9.5% more citation-weighted patents, while newly hired inventors with greater overlap produce 24% more citation-weighted patents compared to their counterparts. Additionally, I find that inventors with low overlap with their pre-merger firms also see post-merger productivity gains, particularly in citation-weighted patents. This further suggests that reallocation allows inventors to transition to firms where their expertise has a higher overlap.

In sum, these findings provide strong evidence that M&As reduce labor market frictions, facilitating job mobility and allowing inventors to find roles where their skills are better used. Reduced labor market frictions and increased technological overlap between inventors and their new employers appear to be key mechanisms driving the observed post-merger increases in innovation productivity for both departing and newly hired inventors. This highlights the broader impact of

M&As on the restructuring of innovative human capital.

Related literature This study contributes to the growing literature on labor restructuring following M&As. Prior research has primarily examined average wages and overall employment at the firm- or plant-level (Lichtenberg and Siegel, 1990, Brown and Medoff, 1988, McGuckin and Nguyen, 2001, Li, 2013). More recent studies use detailed employer-employee administrative data associated with M&A samples in countries such as Brazil (Lagaras, 2021) and Germany (Gehrke et al., 2021), providing insights into employee turnover around the mergers.

These studies offer evidence of labor restructuring after M&As but are limited in two notable ways. First, existing work on labor restructuring around mergers mainly focuses on target employees. While Gehrke et al. (2021) takes a step further by documenting firm-level aggregate employee flows for both the general workforce and managers in the acquirer, target, and merged firms, the focus remains on the merging firms. They pay less attention to the broader impact of M&A on labor restructuring beyond the merging entities. This study addresses this gap by examining a broader set of inventors affected by M&A activities, providing novel evidence on both departed inventors and those newly employed by the combined entity. These groups, who move across firms, offer unique insight into the hypothesis of reduced labor market frictions and play an essential role in the labor restructuring brought about by M&As. Furthermore, while Gehrke et al. (2021) interprets their findings from an organizational form perspective, where acquirer managers better exploit real options than target managers, this study focuses on productivity changes resulting from M&As reducing labor market frictions.

Second, while these results suggest efficiency-driven labor restructuring, they often lack direct evidence due to limited data on individual employee productivity. Existing studies commonly rely on indirect proxies for skill, such as educational attainment (Lagaras, 2021, Ma et al., 2016), or use firm-level measures of labor productivity, such as the ratio of sales to employment or sales to payroll (Tate and Yang, 2015, 2024). In contrast, this study uses patent-based data to construct direct measures of individual productivity. Additionally, existing literature measures human capital relatedness between two firms using industry- (Lee et al., 2018) or firm-specific occupation shares (Gehrke et al., 2021), which may not precisely capture the alignment between an employee and a firm. By using similarity scores between the technological classifications of patents filed by inventors and firms, I provide a more informative measure of employer-employee technological overlap. These individual-level measures allow me to further explore the economic mechanisms behind post-merger inventor restructuring.

This paper also contributes to the growing discussion on M&As and innovation. In recent years, there has been a growing trend in deals involving innovative firms, i.e., firms associated with inventors (See Figure 1). Many firms choose to gain access to innovation by acquiring target firms with the desired technology (Zhao, 2009, Bena and Li, 2014, Mei, 2020). In some cases, big firms acquire small firms that have successfully innovated as a substitute for their in-house R&D (Phillips and Zhdanov, 2013). In other cases, firms intend to acquire research teams in target firms to expand their research capabilities (Ouimet and Zarutskie, 2020). Rather than taking a stand on the motivations behind these innovation-driven acquisitions, this paper provides direct evidence of post-merger turnover and changes in the patenting performance of inventors.

Relatedly, this paper adds to the burgeoning literature that studies inventors in an M&A setting. Though, for the most part, the inventor-level analysis is not the focus of these papers, they do offer valuable insights into how M&As impact inventors. Seru (2014) is the first to provide inventor-level evidence, showing that target inventors either depart or become less productive after mergers, with the latter contributing to reduced innovation activities of acquired firms in diversifying mergers. Mei (2020) points out how inventor turnover varies depending on technological overlap between merging firms. Recent work using inventor-level data explores various aspects of post-merger outcomes: the role of inter-firm inventor collaboration in achieving synergies after mergers (Li and Wang, 2023); the impact of the degree of alignment of acquirers' innovative trajectories with their own inventors' pre-merger knowledge on those inventors' post-merger activity (Chattopadhyay and Karim, 2021); and on target inventors' patenting directions post-merger (Bena et al., 2021). These studies mainly focus on the post-merger patenting performance of a subset of inventors within the combined entity. By contrast, this study takes a broader approach, examining a comprehensive set of inventors affected by M&A activities both within and beyond the merging firms. This provides a more holistic picture of how M&As restructure human capital, offering new insights into the full scope of post-merger inventor reallocation and its impact on their innovation productivity.

The rest of the paper proceeds as follows. Section 2 discusses the data and presents summary statistics of the sample. Section 3 examines the inventor turnovers after M&As. Section 4 presents the results of productivity changes for departing, staying, and newly employed inventors in the post-merger period. Section 5 explores the underlying economic mechanisms. Section 6 concludes.

2 Data and summary statistics

2.1 Patent and inventor data

The patent and inventor data are obtained from the PatentsView platform, an online platform delivering patent data derived from the U.S. Patent and Trademark Office (USPTO). PatentsView provides a comprehensive dataset for each granted patent, including its citations and the technological class it belongs to. Regularly updated since January 1976, it links each patent with its inventors and assignee organizations, along with their precise location information at the latitude and longitude level.[4]

A long-standing issue with patent data is that the USPTO does not track inventors and assignees over time, treating patent applications as singular events. The lack of input consistency results in challenges to associate the same inventor or assignee with more than one patent.[5] To address this issue, PatentsView integrates state-of-the-art disambiguation algorithms to uniquely identify inventors, assignees, and their associated locations. The disambiguation methodology is continually reviewed and updated to incorporate the latest advancements in computer and information sciences, as well as feedback from patent data users.[6]

[4] See introduction of PatentsView: https://www.uspto.gov/ip-policy/economic-research/patentsview

[5] A classic example is the assignee IBM Corp, which appears with various spellings in the USPTO documents, such as 'IBM,' 'IBM Corp,' 'IBM Business Machines Corp.,' and 'IBM Corp INT Business Machines Corporation.'

[6] The USPTO hosted an Inventor Disambiguation Workshop in 2015 and integrated the award-winning disambiguation algorithm into the platform in March 2016. For more details on the disambiguation process, see https://patentsview.org/disambiguation, and for data updates, including major updates for inventor IDs (12/30/2021) and assignee IDs (06/30/2022) used in this study, see https://patentsview.org/release-notes.

2.1.1 Linking firms with patents and inventors

Matching patent data with firms in conventional financial datasets (e.g., Compustat and CRSP) typically relies on fuzzy name matching algorithms between raw assignee names and public company names. Among these efforts, Kogan et al. (2017) provides the most comprehensive bridge table linking patent IDs in USPTO with CRSP firm identifiers (i.e., PERMNO) from 1926 to 2022,[7] extending the NBER Patent Citation Files (NBER dataset). This bridge table has been extensively used in recent studies analyzing innovation activity at the public firm level.

While this bridge table allows linking inventors associated with each patent to public firms, it presents certain limitations for inventor-level analysis. Specifically, the bridge table in Kogan et al. (2017) restricts the sample of patents to those with a unique assignee and those issued during periods when the firm has sufficient information to compute return volatilities. This restriction leads to two potential issues. First, this approach omits certain patents, resulting in missing inventor observations. Second, if an inventor files multiple patents but only a subset is considered, she may be incorrectly linked to firms based solely on that subset. Additionally, the bridge table only links inventors to public firms, making it impossible to track inventors moving between public and private firms, thus limiting the study's scope.

To overcome these limitations and provide a more comprehensive match between firms and inventors, I construct two linking tables. The first table establishes the disambiguated employee-employer link for each inventor (i.e., inventor-assignee) over her active patenting career years. This link is based on the assumption that a patent's assignee is most likely the inventor's employer at the time of filing. Therefore, when an inventor files a patent that is ultimately granted to an organization, I assume that the organization is the inventor's employer in the filing year. The second table dynamically matches PatentsView assignee IDs with CRSP firm identifiers on a yearly basis, building on the bridge table in Kogan et al. (2017). Detailed construction process for these linking tables are provided in Appendix B.

Using these two linking tables, I create a panel dataset that tracks each inventor filing at least two patents over time, linking them to disambiguated assignees and CRSP public firms (if ap-

[7] https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

plicable) from 1976 to 2022. This approach significantly augments the inventor sample, covering 1,157,349 multiple-time patenting inventors in the CRSP public firms — a 20% increase compared to the 960,632 inventors identified when directly using the bridge table in Kogan et al. (2017). Moreover, establishing the link between assignee IDs and CRSP firms includes all patents under the assignee IDs matched to CRSP firms. which expands the observations of patents assigned to the CRSP firms by approximately 43%.

2.1.2 Innovation productivity measures

The most commonly used patent-based variables to measure firms' innovation activity are (1) the number of granted patents filed by the firm each year and (2) the number of citation-weighted patents, where citations are counted from the patent's grant year onward. The former measures the quantity of the innovation, while the latter also accounts for the quality of the innovation. Similarly, I measure an inventor's productivity by counting the number of granted patents and citation-weighted patents each inventor files in a given year.

To address the truncation problem and right-censoring, I normalize the total number of granted patents each assignee firm (or inventor) i files in year t by the average number of patents filed in the same year t and technology class k across all innovative assignees (or inventors) $\overline{M}_{kt}$. The sum of these scaled patents generated by an assignee firm i (or inventor i) in year t is then considered as the adjusted number of patents. Similarly, I standardize each patent's citation count by the average number of citations for patent cohorts in the same year t and the same technology class k (Hall et al., 2001, Bernstein, 2015, Lerner and Seru, 2022), and aggregate this for assignee firm (or inventor) i across all patent classifications filed in year t. If a patent belongs to multiple classifications, it receives equal weight across them, adding up to one. This process also accounts for heterogeneity across time and industry. The following equations summarize the process, where M = 125 (based on the USPTO CPC class), and N_{kt} is the total number of granted patents applied in year t and class k.

$$AdjPatent_{i,t} = \sum_{k}^{M} \frac{n_{ikt}}{\overline{M}_{kt}} \tag{1}$$

$$AdjCPatent_{i,t} = \sum_{k}^{M} \frac{\sum_{j}^{n_{ikt}} Citation_j}{\sum_{j}^{N_{ikt}} Citation_j / N_{kt}} \tag{2}$$

In addition to using citation counts as a measure of a patent's scientific value, Kogan et al. (2017) introduces a measure of the private economic importance of innovations by analyzing stock price movements following a patent's grant date. This measure, while positively correlated with citation-weighted patent counts, captures additional information which is most likely related to the patent's private economic value, as indicated by its stronger association with firm growth and creative destruction. Furthermore, since this measure is expressed in inflation-adjusted dollars (using the CPI), it allows for comparisons across time and industries. To assess the economic value of patents filed by a firm or inventor in year t, one can sum the real value of the patents they file in that year. However, this measure is limited to patents with a unique assignee, those issued while the firm has non-missing market capitalization in CRSP, and cases where return volatilities can be calculated, thus covering only a subset of the patents examined in this study.

2.2 Innovative deals

2.2.1 M&A sample construction

I use Thomson Financial's SDC Platinum Dataset to form the M&A sample. The sample includes all completed deals announced after January 1, 1984, and completed before December 31, 2017, that are classified as "Acquisition of Assets (AA)", "Merger (M)", "Acquisition (A)", or "Acquisition of Majority Interest (AM)". The sample begins in 1984, as SDC data is considered fairly accurate and complete from that year onward (Barnes et al., 2014). It ends in 2017, which allows for the examination of post-merger innovation outcomes within a five-year window after deal completion, covering patents filed up until 2022. Then, I follow the conventions in M&A studies and impose the following filters. First, both acquirer and target firms are U.S. public firms covered by the CRSP database with a unique PERMNO. Second, acquirers hold less than 50% of the target shares prior to the deal announcement and own 100% target shares after the transaction. Third, both acquirer and target firms are innovative firms, defined as firms with at least one inventor one year before the deal announcement.[8]

2.2.2 Time trend

Figure 1 plots the trend of completed innovative deals from 1984 to 2017. The red (blue) bar shows the number of innovative (other) deals each year, while the yellow line shows the ratio of innovative deals among all CRSP-matched public deals during the sample period. The proportion of innovative deals shows a clear upward trend over time, with a significant rise around 2008-2010 and another peak around 2014-2015, despite the overall decline in total deals.[9]

[*Insert Figure 1 here*]

This upward trend may be driven either by an increase in innovative firms engaging in M&As or by a growing proportion of innovative public firms over time. To explore this further, Figure 2 shows the composition of innovative versus non-innovative firms. It reveals that the proportion of innovative firms among all CRSP firms has remained relatively stable. Given the stable proportion of innovative firms, the upward trend in innovative M&A deals is more likely driven by increased M&A participation among these firms rather than by their growing presence. This trend further highlights the importance of innovative deals.

[*Insert Figure 2 here*]

2.2.3 Industry coverage

There is a reasonable concern about the industry coverage of innovative deals, given the unequal distribution of patenting firms across industries (Lerner and Seru, 2022). Figure 3 illustrates the industry distribution of innovative versus other merging firms across all deals during the sample period. I collect each merging firm's historical SIC code from one year before the deal

[8] The process of matching firms with inventors is discussed in section 2.1.1.

[9] This trend is consistent with Mei (2020), which defines a firm as innovative at year t if the firm is active in patenting during a three-year window $[t-3, t-1]$.

announcement and map them to the Fama-French 12 Industry Classification. Innovative firms are defined as merging firms associated with at least one inventor one year before the deal announcement date.

Specifically, Panel A shows the industry distribution of the unique number of innovative acquirers (blue bar) versus other acquirers (red bar) during the sample period. Panel B shows the industry distribution of the unique number of innovative target firms (blue bar) versus other target firms (red bar) during the sample period. Both acquirer and target innovative firms are present in nearly all industries, similar to other merging firms, but they are more concentrated in manufacturing, business equipment, and healthcare.

[*Insert Figure 3 here*]

2.2.4 Summary statistics

After requiring that both the acquirer and target firms 1) have available information from the CRSP/Compustat Merged Database, 2) have a unique PERMNO, 3) report a positive value for the book value of total assets and equity, and 4) have available historical information one year before the deal announcement, the sample includes 845 innovative deals.

Panel A in Table 1 presents the summary statistics of the deal-level characteristics for innovative deal sample over the same period. Among the deals, 38% of innovative deals are diversifying deals, where the acquirer and target firms are in different industries (as defined by 2-digit SIC codes). Additionally, 38% of innovative deals are paid entirely in cash, while 33% of innovative deals are paid entirely in stock. The relative size of innovative deals, defined as the deal value over the market value of acquirer firms at $ayr - 1$, is 30%.

Panel B reports the summary statistics of 845 innovative acquirer and target firms with available information in CRSP (and unique PERMNOs) one year before the deal announcement date. Financial variables of acquirer and target firms are collected from Compustat/CRSP dataset, the detailed variable definitions can be found in Appendix A. Serial acquirers are counted as separate observations. Asterisks denote the significance of the mean differences between innovative acquirers and targets. Compared to innovative target firms, innovative acquirers are larger, have more inventors and patents and show higher ROAs, OCF-to-asset ratios, and Tobin's Q before the merger. They also hold more tangible assets but less cash relative to total assets and have lower R&D ratios. This comparison reflects the innovative target firms' focus on investing in intangible assets.

[*Insert Table 1 here*]

2.3 Inventors involved in innovative deals

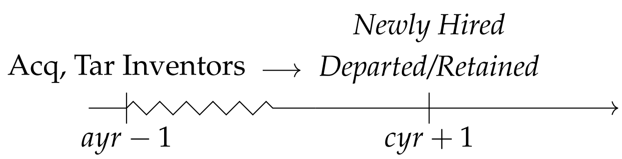
2.3.1 Summary statistics

To construct a sample of inventors involved in innovative deals, I link inventors to public merging firms either one year before the deal announcement date or one year after the deal completion date, using the table built in Section 2.1.1. Panel A of Table 2 summarizes those inventors directly impacted by the merger. Among 296,302 unique inventors, the average inventor is associated with 2.45 non-individual assignees and remains active for 15.95 years. An average inventor files 9.57 patents and 19.35 citation-weighted patents, adjusted for the patent's application year and technology class. They also file 2.12 high economic value patents on average, defined as those in the top 15th percentile of private economic value within their cohort in the same year and technology class.

For the inventor-level analysis tracking labor outcomes and performance changes after deal completion, I apply an additional filter to ensure that each inventor's active patenting career spans the merger period. This filtered sample captures more productive and mobile inventors. As shown in Panel B of Table 2, these inventors are associated with more assignees (2.69 vs. 1.60) and have longer active patenting careers (18.25 vs. 7.92 years) compared to other inventors in the full sample (Panel C). They also file more patents (11.01 vs. 4.53 in adjusted numbers), more citation-weighted patents (22.65 vs. 7.82 in adjusted numbers), and more high economic value patents (2.43 vs. 1.02). Additionally, they receive more citations per patent (18.57 vs. 15.14). The differences across all variables are significant. Notably, the selected inventor sample used in the main analysis represents 78% (230,388 out of 296,302) of the full inventor sample, suggesting that it is relatively representative and helps mitigate concerns of selection bias.

[*Insert Table 2 here*]

2.3.2 Categorizing inventors



I define the merger window as the period beginning one year before the deal announcement year and extending to one year after the deal completion year, i.e., $[ayr - 1, cyr + 1]$, to minimize the influence of other irrelevant factors.[10] As illustrated visually above, I first identify acquirer (target) inventors as those associated with the acquirer (target) firms one year before the deal announcement year ($ayr - 1$). These inventors are further classified as either retained inventors or departed inventors based on whether they remain associated with the combined entity after deal completion (i.e., $cyr + 1$). Newly hired inventors are defined as those associated with the combined entity in $cyr + 1$ but not with either the acquirer or target firms in $ayr - 1$.

3 Inventor turnovers around M&A

In this section, I document the post-merger restructuring of inventors from merging firms, along with those hired externally, and the overall effect on inventor team size.

I hypothesize that inventor turnover in target firms increases post-M&A for two reasons. First, Maksimovic et al. (2011) documents a significant post-merger asset restructuring relative to the industry-year matched firms or assets, with acquirers selling or closing nearly 30% of target assets. This suggests that acquirers may selectively retain inventors, leading to higher turnover. Second, M&As reshape organizational structures, which can reduce labor market frictions, such

[10] Some researchers examining inventor turnover in other settings employ a rather flexible approach, where an inventor is considered a leaver as long as she filed at least one patent at the sample firm before the corporate event, and at least another at a different firm after the corporate event (Bernstein, 2015, Brav et al., 2018, Cunningham et al., 2021). However, this approach faces a potential problem, that is, if the filing date of the inventor at a different firm after the corporate event is too far away from the corporate event date, then the inventor might have moved for reasons unrelated to the deal.

as employee inertia, thereby lowering the opportunity cost for target inventors to search for new jobs. As a result, target inventors' own job decisions could contribute to the increased mobility following M&As.

The impact on inventors at acquirer firms is less predictable. If acquirer inventors have overlapping skills with target inventors, some may be displaced. However, the formation of new research teams between acquirer and target inventors (Li and Wang, 2023) could decrease the departure rate of acquirer inventors.

The effect on inventors newly hired by the combined entity is also ambiguous. On the one hand, merging two firms can create a unique research environment with strengths in specific areas, increasing the marginal benefit for external inventors to seek new opportunities. On the other hand, the need to hire external inventors may decline as the combined entity has effectively "acquire-hired" the target's inventor team, despite some departures. Thus, the net effect on the percentage of inventors newly hired by the combined entity post-merger remains an empirical question. Lastly, changes in the inventor team size within the combined entity reflect the overall effect of turnover across all inventor groups (i.e., stayers, leavers, and new hires) in the merging firms.

3.1 Empirical setup

I compare inventor turnover rates within the sample firms to those of a control group of firms not involved in acquisitions. Following Golubov and Xiong (2020), I use a variable ratio ($k : 1$) nearest neighbor matching algorithm (with replacement) to identify control firms for the acquirer (target) firms.

To estimate the propensity score of a firm being involved in a merger, conditional on a set of covariates $X_{i,ayr-1}$, I use the following Probit regression:

$$Pr(Y = 1|X) = \Phi(X_{i,ayr-1}^{T}\beta + u_{SIC_2} + u_{ayr}), \tag{3}$$

where the covariates X include a standard set of variables that are known determinants of merger involvement (Golubov and Xiong, 2020). These variables encompass firm-level characteristics in the year before the deal announcement, such as ROA, leverage ratio, asset tangibility, OCF-to-Asset ratio, R&D intensity, cash ratio, the logarithm of total assets (in 2019 real terms), Tobin's Q, and the logarithm of ask-bid spread. Importantly, the firms in my sample are not only patenting firms but are also associated with at least one inventor before the mergers. Given the innovative nature of these firms, I augment the covariate set with additional variables: the logarithm of one plus the number of patents (adjusted for technology classes and filing years) filed by firm i in the five years leading up to year $ayr - 1$ ($Ln(1 + AdjPatents\_5Y)$), and the logarithm of one plus the number of inventors associated with the firm in year $ayr - 1$ ($Ln(1 + Inventors)$). I also include industry fixed effect (FE) (2-digit SIC) and deal announcement year FE (u_{SIC_2} and u_{ayr}) in the Probit regression, following Chari et al. (2012) and Golubov and Xiong (2020).

I then use a variable ratio ($k : 1$) nearest neighbor matching algorithm (with replacement) based on the estimated propensity score (Smith, 1997, Rubin and Thomas, 2000). While selecting more matches for each treated observation reduces variance, it also increases bias. Linden and Samuels (2013) suggests that the optimal number of matches maximizes the number of matched sets while maintaining overall covariate balance. Following this guidance, I choose $k = 2$ for matching the sample firms.

To construct the candidate pool for matched firms of acquirer (target) firms, I impose the following conditions: (a) candidate firms in year t must not be involved in any innovative mergers within $[t - 5, t + 5]$,[11] and (b) candidate firms in year t must be associated with at least one inventor. For each acquirer (target) firm, I then select up to two firms from the candidate pool that are in the same industry, in the same year (i.e., in $ayr - 1$), and have the closest propensity score to the acquirer (target) firm.[12]

The goal of the matching is to create a balanced control sample of acquirer and target firms comparable to the treatment firms in terms of their observable characteristics prior to the merger. Table 3 reports the results for propensity score matching of acquirer firms (Panel A) and target firms (Panel B). Standard errors are in parentheses in Column (1), and t-statistics are in paren-

[11] A firm not involved in any mergers in t means that $t \notin [ayr, cyr]$, where ayr is deal announcement year and cyr is deal completion year.

[12] The goal is to select two firms with the closest propensity scores from the same industry and year as the treated firm. However, in some cases, fewer than two candidate firms may be available, resulting in fewer matches.

theses in Columns (4) and (6). Column (1) presents the estimation coefficients from the Probit regression. The set of included covariates differs slightly between acquirer and target firms to achieve a balanced sample. Most variables are strong predictors of whether a firm becomes an acquirer or target.

For financial characteristics, firms with higher total assets, ROA, Tobin's Q, R&D intensity, along with lower asset tangibility, OCF-to-asset ratio, and leverage ratio, are more likely to be acquirer firms. In contrast, firms with higher cash holdings, more assets, higher R&D intensity, fewer tangible assets, and a lower Tobin's Q are more likely to be targets. Notably, the variables related to pre-merger innovation activity, which I add to the standard set of covariates, are statistically significant. Specifically, firms with more inventors are more likely to be acquirers, while firms with fewer inventors but more patents filed in the five years leading up to $ayr - 1$ are more likely to be targets. The pseudo-R^2 of the propensity score is 16% for the acquirer firms and 6% for the target firms.

Column (2) shows the mean variables for acquirer (or target) firms, as in Panel B of Table 1. Columns (3) and (4) display the mean variables for candidate firms and the mean differences between treated and candidate control firms before matching, where most differences are statistically significant. Columns (5) and (6) present the same information after matching. After matching, as shown in Column (6), these differences are significantly reduced, with only a few remaining: R&D intensity, and the logarithm of bid-ask spread for acquirer firms.

To further evaluate the effectiveness of the matching, I assessed the standardized mean differences, a method recommended by the matching literature over relying solely on statistical significance tests. The standardized mean difference is calculated by dividing the mean difference by the standard deviation of the covariate in the treated group ($\frac{\bar{X}_t - \bar{X}_c}{\sigma_t}$). For regression adjustments to be reliable, the absolute standardized differences should be less than 0.25 (Rubin, 2001). In this analysis, the absolute standardized mean differences are 0.112 for R&D intensity and 0.095 for $Log(spread)$ in acquirer firms — both well below the 0.25 threshold. This additional check demonstrates a significant improvement in balance after matching.

[*Insert Table 3 here*]

Figure 4 presents density plots of the propensity scores for merging firms and control firms. For both acquirer and target firms, the density plot of the propensity scores for matched firms (represented by the dash-dotted line) closely aligns with that of the treated firms (denoted by the solid line), compared to the candidate firms before matching (represented by the dashed line). In summary, the balance check results indicate that the matching procedure successfully creates a balanced pseudo-sample of acquirer and target firms, making them virtually indistinguishable from the treated firms in terms of observable covariates.

[*Insert Figure 4 here*]

3.2 Main findings

After constructing a balanced set of control firms for acquirer and target firms, I use the following baseline Difference-in-Differences (DiD) specification to examine the effect of M&As on inventor turnover in these firms:

$$y_{i,t} = \alpha_s + \alpha_{t,ind} + \beta_1 I(Post) + \beta_2 I(M\&A) + \beta_3 I(M\&A) \times I(Post) + \gamma X_{i,t-1} + e_{i,m,t}. \tag{4}$$

The dependent variable $y_{i,t}$ represents various measures of inventor mobility within firm i (expressed as percentages), observed over two consecutive windows of equal length. The post-merger window spans from one year before the deal announcement to one year after the deal completion $[ayr - 1, cyr + 1]$, while the pre-merger window covers the same length ending in the year prior to the deal announcement $ayr - 1$. The dummy variable $I(Post)$ equals one if inventor turnover is calculated within the post-merger window and zero if calculated in the pre-merger window. The indicator variable $I(M\&A)$ is set to one if the firm is involved in an innovative M&A and zero otherwise. The covariates $X_{i,t-1}$ include all variables used in the sample balance check in Table 3. α_s represents the stack fixed effects, where each deal and its matched pseudo-pairs are grouped. In each stack, the true deal receives a weight of one, while each pseudo pair receives a weight of $1/n$, where n denotes the number of matched firms for a given acquirer (target) firm (Stuart, 2010). $\alpha_{t,ind}$ represents year $\times$ industry FE, with the year denoting the one year before the deal announcement. The standard errors are clustered at the matching group level. Columns (1) and (3) in Table 4 report the results.

Alternatively, I use a specification that includes the deal-firm fixed effects α_m, which absorbs the firm-level variables and the coefficient of $I(M\&A)$, as shown in Eq. (5). The results are reported in Column (2) and (4) in Table 4. The standard errors are clustered at the deal level.

$$y_{i,t} = \alpha_m + \alpha_{t,ind} + \beta_1 I(Post) + \beta_3 I(M\&A) \times I(Post) + e_{i,m,t} \tag{5}$$

Panel A of Table 4 presents the turnover rates of target and acquirer inventors following M&As, where the dependent variable is the departure rate of inventors in the (pseudo) acquirer or (pseudo) target firms. Acquirer (target) inventors are defined as those associated with the acquirer (target) firms at the start of the examined window. I track these inventors to determine the percentage who remain active (i.e., continue filing patents) but leave the combined entity by the end of the examined window (i.e., no longer associated with either the acquirer or target firm).

The results indicate a significant increase in the departure rate of target inventors, with a rise of 5.6 to 5.9 percentage points compared to control firms. In contrast, the departure rate for acquirer inventors drops by 1.4 to 2.3 percentage points. These findings suggest that M&As impact target inventors more than acquirer inventors. The increased departure rate among target inventors is potentially driven by selective retention practices or reduced labor market frictions that lower the opportunity cost of job searching for target inventors. Conversely, the decreased departure rate among acquirer inventors suggests greater job security, possibly due to better integration into the acquirer's existing innovation structure or increased cooperation with target inventors joining the combined entity (Li and Wang, 2023).

Panel B of Table 4 presents the results on inventor turnover for new hires in the combined entity after deal completion (i.e., $cyr + 1$) and the overall percentage change in the inventor team size within the $[ayr - 1, cyr + 1]$ window. The change in team size is calculated by comparing the number of inventors in the combined entity one year after deal completion to the sum of inventors in both the acquirer and target firms before the merger. Specifically, it is computed as $\frac{\#Inventors_{Combined,cyr+1}}{\#Inventors_{Acq,ayr-1} + \#Inventors_{Tar,ayr-1}} \times 100\%$, reflecting the relative change in team size post-merger.

The control sample comprises pseudo-pairs consisting of matched pseudo-acquirer firms and the actual target firms. The percentage of new hires in the combined entity decreases by up to 0.2 percentage points compared to pseudo-combined entities, a change that is neither statistically nor economically significant. This suggests that M&As have little effect on the percentage of new inventors hired by the combined entity.

Finally, the change in inventor team size shows an increase of 2.1 to 3.9 percentage points relative to pseudo-deals, but this too is not statistically significant. Overall, M&As primarily affect turnover among existing inventors, especially within target firms, rather than expanding the inventor team through new hires.

[*Insert Table 4 here*]

3.3 Parallel trend

To ensure the internal validity of the DiD models, the parallel trends assumption must hold. This assumption implies that both the treatment and control groups would have followed similar trends over time if the treatment had not been treated. However, measuring inventor turnovers across variable deal windows introduces complexity in testing this assumption.

To address this, I calculate outcome variables over specific time windows relative to the main analysis window $[ayr-1, cyr+1]$. Each window has the same length l as $[ayr-1, cyr+1]$, which differs by deal. Specifically, I define $t=-1$ as the window ending in year $ayr-1$, spanning the same length as $[ayr-1, cyr+1]$. Similarly, $t=1$ denotes the window starting in year $cyr+1$, spanning $[cyr+1, cyr+1+l]$. The remaining windows are defined as rolling windows, shifted one year to the left (or right). For instance, $t=-2$ corresponds to $[ayr-2-l, ayr-2]$, and $t=2$ corresponds to $[cyr+2, cyr+2+l]$. Additionally, I ensure that neither treated nor control firms are involved in any mergers during windows other than $[ayr-1, cyr+1]$.

Figure 5 provides a visual check of parallel trend by plotting group means and 95% confidence intervals for inventor turnover-related outcomes in merging firms and their matched pseudo firms (from propensity score matching in Section 3.1). The visual evidence suggests that both treated and control firms follow parallel trends prior to the acquisition for all inventor turnover-related outcome variables.

[*Insert Figure 5 here*]

3.4 Why not using failed bids as quasi-experiment?

To find comparable firms, I use exact matching on key covariates such as year and industry, followed by a variable ratio nearest neighbor matching algorithm (with replacement) based on the estimated propensity scores within the matched groups. Although failed bids are often used as a quasi-experimental design in M&A and innovation studies (Bena and Li, 2014, Seru, 2014, Li and Wang, 2023), I choose not to adopt this method for two key reasons.

First, the failed bids sample may not serve as an ideal counterfactual in this context. Once a deal is announced, its effects on inventors are likely already in motion. Inventors at target firms may begin seeking new opportunities due to anticipated disruptions, even if the deal ultimately falls through. This is consistent with findings from Seru (2014), which show that the increased likelihood of inventors leaving is present in both completed and failed bid samples.

Second, the small sample size of failed bids raises significant bias concerns. Unlike studies focused on firm-level innovation, this study examines inventors within merging firms. Requiring both acquirer and target firms in the failed bids sample to be associated with inventors before and after M&As further reduces the sample size, exacerbating small sample bias. For instance, Li and Wang (2023) report only 18 eligible withdrawn bids in a similar setting, while I identify only 39 in this study. This limited sample size makes it difficult to construct a balanced control group and conduct robust causal inference.

4 The productivity change of inventors following the merger

In this section, I analyze the impact of M&As on the innovation productivity of two groups of inventors affected by the merger: (1) all staying inventors within the combined entity, including those retained from the acquirer or target firms and newly hired post-merger, and (2) inventors who departed from either merging firm.

4.1 All staying inventors in the combined entity

Devos et al. (2009) show that the post-merger efficient resource reallocation is a major source of merger gains for the combined entity. Empirical studies, such as those by Maksimovic and Phillips (2001), Maksimovic et al. (2011), and Schoar (2002), track post-merger performance changes of individual plants involved in mergers, and find evidence of enhanced productivity in the acquired and retained plants. This suggests that firms exploit their comparative advantages in operating target plants to generate synergies.

To explore whether human capital reallocation plays a similar role in post-merger outcomes, I investigate how the productivity of staying inventors — whether retained from acquirer or target firms, or newly hired — changes following the merger.

4.1.1 Empirical setup

The main regression specification is shown in Eq. (6), using inventor-year observations. The dependent variable $y_{j,t,m}$ represents patent-based measures of individual inventor j's innovation productivity in deal m for year t: (1) the number of adjusted granted patents, (2) the number adjusted of citations-weighted patents, and (3) the sum of real economic value for patents, as per Kogan et al. (2017), filed by the inventor j year in year t. if an inventor does not file any patent in a given year, the patent-based measures are assigned a value of zero. Since the outcome variables are count-based, I follow Cohn et al. (2022) and use a Poisson regression model with filing year fixed effects (α_t) and deal-inventor fixed effects ($\alpha_{j,m}$), as in Eq. (6).[13]

$$E[y_{j,t,m}|\mathbf{x}] = e^{\mathbf{x}\boldsymbol{\beta}} = e^{\beta_0+\beta_1 I(Post)+\beta_2 I(M\&A)\times I(Post)+\alpha_t+\alpha_{j,m}+e_{j,m,t}} \tag{6}$$

To construct the matched inventor samples, staying (departed) acquirer (target) inventors are matched with staying (departed) inventors from the matched acquirer (target) firms. Newly hired inventors are similarly matched with their counterparts from the matched pseudo-acquirer firms.

[13]When working with count-based outcome variables, Cohn et al. (2022) shows that the common practice of adding a constant to the outcome variable and then estimating log-linear OLS regressions can be problematic. The estimates can easily have the wrong sign and have no economic meaning. They suggest using a fixed-effects Poisson regression, which produces unbiased and consistent estimates under standard exogeneity conditions.

$I(M\&A)$ is a dummy variable equal to one if the inventor is associated with a merging firm one year before the deal announcement date, and zero otherwise. $I(Post)$ is a dummy variable set to one when the outcome variable is measured in the post-merger period — defined as the period from five years before the deal announcement (or the earliest year the inventor is associated with the assignee firm as she is in $ayr-1$, whichever is more recent) to five years after the deal completion (or the latest year she is with the assignee firm as she is in $cyr+1$, whichever is earlier). This ensures an inventor's productivity is measured exclusively during their time with the merging firms. In contrast, previous studies consider the inventor's entire career, which may introduce noise if they are not consistently associated with the firms over a longer period (Seru, 2014, Brav et al., 2018).

4.1.2 Main findings

Panel A of Table 5 presents the innovation performance changes for staying acquirer and target inventors. Staying inventors from acquirer firms show a significant boost in innovation performance compared to their counterparts in matched firms, with a 6.2% increase in patent filings, 23% more citation-weighted patents, and a 2.2% rise in the economic value of their patents. Conversely, target staying inventors experience a significant decline in productivity, filing approximately 26% fewer patents, 26% fewer citation-weighted patents, and generating 30% less economic value compared to matched target inventors.

Panel B reports the innovation performance of inventors newly hired by the combined entity post-merger. The real value measure is unavailable for some inventors due to limited coverage, with only about 50% of the data available, as many inventors may have come from private assignee firms. After the acquisitions, newly hired inventors in the combined entity file 4.7% fewer patents but produce 13% more citation-weighted patents than newly hired inventors in the matched acquirer firms, suggesting an improvement in the quality of their innovation output despite a reduction in quantity.

To benchmark the performance of all inventors in the combined entity post-merger, I compare their output to inventors from the matched acquirer firms one year after the pseudo deal completion. Inventors in the combined entity file 4.5% more patents, 21% more citation-weighted patents, and generate 2.5% higher economic value from their patents relative to the control sample, indicating a notable improvement in both the quantity and quality of innovation.

Overall, these findings highlight the significant role of inventor restructuring in driving productivity gains. By integrating acquirer, target, and newly hired inventors, the combined entity fosters greater innovation, particularly in citation-weighted patents and economic value. ThThe improvements are largely driven by acquirer and newly hired inventors, experience a decline in innovation productivity. This broader view reconciles recent research that focuses on specific inventor groups and provides additional economic insights. For instance, the decline in target inventor productivity aligns with Seru (2014), while Li and Wang (2023) find that collaborations between acquirer and target inventors lead to more groundbreaking patents, consistent with the result of overall increase in innovation productivity in this study. The findings also highlight the contribution of newly hired inventors, offering a more comprehensive view of post-merger innovation outcomes.

[*Insert Table 5 here*]

4.2 Departed inventors following M&As

In addition to restructuring physical assets, prior literature has also documented changes in post-merger performance for sold-off plants. Maksimovic et al. (2011) report that the sold plants' productivity shows positive changes, but they are much less significant than that of the kept plants. This suggests that acquirers may keep the target plants where they have comparative advantages in operating, but shed the assets otherwise.

However, the impact of M&As on *departed inventors* — a less studied area — remains uncertain ex-ante. On the one hand, whether inventors leave voluntarily or involuntarily, reduced labor market frictions from M&As may help inventors better assess their strengths and make optimal job decisions, potentially boosting innovation productivity. This contrasts with sold-off plants, where performance is mostly tied to the new owners' operational capabilities. On the other hand, job transitions could disrupt innovation, particularly for inventors forced to leave, leading to a decline in productivity. This section provides novel evidence on the post-merger productivity changes of inventors who depart from merging firms.

Table 6 presents the performance changes of departed inventors relative to their counterparts in control firms, using the same specification as in Eq. (6). The results show that, compared to their control peers, departed inventors file 2.9% more patents and 7.3% more citation-weighted patents following M&As, both statistically significant at the 1% level (Columns (5) and (6)). This suggests that inventors switching jobs post-merger experience productivity gains. These gains are primarily driven by those leaving acquirer firms, who file 4% more patents and 7.9 % more citation-weighted patents than their matched peers (Columns (1) and (2)). Note that the real economic value of patents, as a measure of innovation performance, is also excluded from the analysis for departed inventors due to limited data availability for private firms where departed inventors may relocate, with only around 50% coverage.

Departed target inventors, however, exhibit asymmetric performance changes. While they file 6.5% fewer patents compared to their counterparts in matched firms, their citation-weighted patents show a slight, albeit statistically insignificant, positive change (Column (3) and (4)). This suggests that the negative impact of M&As on departed target inventors is less severe than the substantial decline observed in staying target inventors. The modest effect on citation-weighted patents suggests that these inventors may continue to contribute in their new positions.

Overall, these findings highlight the complex nature of human capital restructuring in M&As. Unlike sold-off plants, where productivity gains are constrained by operational control, inventor productivity appears to be shaped not only by internal restructuring but also by individual career choices and opportunities in the broader labor market.

[*Insert Table 6 here*]

5 Economic mechanism

5.1 Determinants of inventors' post-merger labor outcomes

I observe significant inventor turnover after M&As, yet little is known about the factors that influence whether an inventor stays or leaves the merged firm. Specifically, how do acquirers restructure inventors from both merging firms post-merger? And how do inventors' personal job decisions intersect with this restructuring process? Moreover, I find that acquisitions do not prevent the combined firms from hiring new inventors. This raises an intriguing question: why do acquiring firms continue to recruit external inventors, even after absorbing inventors from the target firm, despite some departures? In other words, how do these newly hired inventors differ from the existing ones, and in what dimensions?

In this section, I address these questions by analyzing the determinants of post-merger labor outcomes for two groups: 1) inventors within the merging firms, and 2) newly hired inventors.

5.1.1 Two non-mutually exclusive channels

To understand the determinants of labor outcomes for inventors within the merging firms, I propose two non-mutually exclusive channels. First, acquirers may be ex-ante interested in a subset of target inventors working in specific technological domains (*matching channel*). For example, they may prefer to retain target inventors whose patenting expertise aligns closely with the target firms' core business areas, especially when those technological strengths are the primary motive for the acquisition. Alternatively, acquirers may favor inventors from both the acquirer and target firms whose patents align more directly with their own core business, where they have a higher comparative advantage. Second, acquiring firms may aim to retain inventors based on their ex-ante productivity and streamline operations by laying off lower-quality or redundant employees (Lee et al., 2018, Lagaras, 2021). This parallel mechanism echoes findings from Maksimovic et al. (2011), where less productive plants are more likely to be divested post-merger.

To test the role of matching channel, I construct two variables to measure the inventor-firm technological overlap. The first variable, *SameCore*, is a dummy variable equal to one if the firm's core business aligns with the inventor's primary area of expertise, and zero otherwise. Both the firm's core business and the inventor's core expertise are identified by the patent class with the highest number of patents filed up to one year before the deal announcement (Li and Wang, 2023). The second variable, $CosineSimilarity$, quantifies the degree of inventor-firm technological overlap based on the technology class of their patents (Jaffe, 1986, Bena and Li, 2014, Ma, 2020, Mei, 2020). To calculate this, I first create a class-based innovation vector for each patent, where the vector takes a value of one for the relevant technology class and zero for others. Next, I aggregate these vectors across all patents belonging to the firm (or inventor), constructing a firm-level (or inventor-level) innovation vector. Finally, I compute the cosine similarity between the firm's innovation vector (TC_i) and the inventor's innovation vector (TC_j), as shown in Equation (7). A higher cosine similarity score indicates greater technological overlap, reflecting a stronger technological match between the firm and inventor.

$$TechProxi_{i,j} = \frac{TC_i \cdot TC_j}{|TC_i| \cdot |TC_j|} \tag{7}$$

To test the role of screening, I use patent-based measures of an inventor's pre-merger innovation productivity, denoted as $Prod_{i,t-1}$, for inventor i, using (1) log of one plus the number of patents filed (adjusted for filing year and technological class); (2) log of one plus the number of citations received by patents filed (adjusted for filing year and technological class) for all patents filed by the inventor up to one year before the deal announcement. This productivity variable captures the inventor's innovative output before the merger.

I use linear probability regressions to analyze how factors associated with the proposed channels influence post-merger labor outcomes for affected inventors, as shown in Eq. (8). For inventors in the merging firms, the dependent variable $y_{i,j,t}$ equals one if inventor j leaves the merged firm i one year post-merger, and zero otherwise. For newly hired inventors, $y_{i,j,t}$ equals one if the inventor is newly hired by the combined entity one year after deal completion, and zero if they are retained from either merging firm.

$$\begin{aligned} y_{i,j,d,t} = &\alpha_d + \alpha_t + \beta_1 Match_{i,j,t-1} \times Prod_{i,t-1} \\ &+ \beta_2 Match_{i,j,t-1} + \beta_3 Prod_{i,t-1} + \gamma X_{i,j,t-1} + e_{i,j,t} \end{aligned} \tag{8}$$

The primary independent variables are the technological overlap between the inventor and the merging firm, denoted as $Match_{i,j,t-1}$, and the inventor's pre-merger productivity, $Prod_{i,t-1}$. Control variables include inventor-specific characteristics such as network size, specialization, and active patenting years, all measured up to year $t-1$ (Li and Wang, 2023, Baghai et al., 2024). The model includes deal fixed effects (α_d) and pre-announcement year fixed effects (α_t), with standard errors clustered at the deal level. Results for the matching channel are presented in Table 7 (muting β_1 and β_3), the screening channel in Table 8 (muting β_1 and β_2), and the interaction of both channels in Table 9.

[*Insert Table 7 here*]

[*Insert Table 8 here*]

[*Insert Table 9 here*]

5.1.2 Staying v.s. departing inventors

The *matching channel* plays an important role in shaping post-merger labor outcomes for inventors from the merging firms, as shown in Table 7. The significant negative coefficients in Columns (1) and (2) indicate that acquirer inventors with higher technological overlap with their firms are less likely to leave. Specifically, an acquirer inventor whose core patenting expertise aligns with the acquirer firm's core business is 1.8% less likely to depart compared to an inventor working in a different area, corresponding to an 11.15% decrease in the unconditional acquirer inventor departure rate of 11.15%. Moreover, a one standard deviation increase in cosine similarity between the acquirer inventor and the firm leads to a 7.5% reduction in the departure rate.

The results also show that acquirers tend to retain target inventors who work closely in the target firm's core technological areas (Column (3)) but not necessarily those aligned with the acquirer's own technological areas (Columns (5) and (6)). A target inventor is 1.5% less likely to leave if their expertise aligns with the target's core business, translating to a 5.47% reduction from the unconditional target inventor departure rate of 27.42%. However, the broader measure of technological overlap, based on cosine similarity of all patents filed, does not show a significant relationship with target inventors' post-merger retention (Column (4)). Additionally, working in areas closely related to the acquirer's technological areas does not significantly impact whether target inventors remain with the combined entity, suggesting that acquirers may be more focused on retaining inventors whose expertise is central to the target firm's technological strengths.

In contrast, the evidence in Table 8 provides limited support for the screening channel in inventor restructuring within merging firms. More productive acquirer inventors, based on both patent count and citation-weighted patents, are slightly more likely to depart post-merger, as shown in Columns (1) and (2). However, the economic significance of these effects is small — a one standard deviation increase in the number of patents (citation-weighted patents) corresponds to a 0.95% (0.79%) increase in the likelihood of departure. For target inventors, the pattern is somewhat stronger, as greater patent output corresponds to a 3% increase in the likelihood of leaving for a one standard deviation increase in patent output. However, this effect is absent when productivity is measured by citation-weighted patents. These findings suggest that, on average, M&As do not guarantee the retention of inventors with higher pre-merger productivity.

Interestingly, the combined effect of the screening and matching channels emerges as a strong and consistent predictor of inventors' post-merger labor outcome. Table 9 shows that the interaction between pre-merger productivity and technological overlap produces significant negative coefficients across all specifications. This suggests that for inventors from merging firms whose technological expertise aligns with either their original firm or the acquirer's core business, those who are more productive pre-merger are less likely to leave the merged entity. This effect is more pronounced for target inventors than acquirer inventors. In contrast, for those working in peripheral technological areas, higher pre-merger productivity decreases the likelihood of retention. Overall, there is a clear sorting effect based on both pre-merger productivity and inventor-firm technological overlap.

In summary, the restructuring of inventors within merging firms provides more evidence for the matching channel relative to the screening channel. Turnover tends to be higher for inventors whose patenting expertise are less aligned with those of their employer, particularly for acquirer inventors. The combined effect of the screening and matching channels strongly predicts post-merger labor outcomes for inventors in the merging firms. Acquirers are particularly effective at retaining productive target inventors whose expertise aligns with the target's patenting areas, as well as those whose expertise overlaps with the acquirer's own patenting areas.

Moreover, an analysis of inventor-specific traits shows that inventors with larger networks, greater specialization, and fewer years of patenting experience pre-merger are less likely to leave the combined entity. These trends hold for both acquirer and target inventors.

These findings highlight the complex dynamics of post-merger inventor restructuring, which differs from physical asset reallocation in M&As, where acquirers typically retain productive plants (McGuckin and Nguyen, 1995). The divergence comes from the fundamental differences between managing physical assets and innovative human capital. While firms may attempt to retain productive inventors, their ability to do so is limited by the inventor's personal decisions. For instance, inventors may choose to leave if they prefer smaller firms that offer more opportunities for their ideas (Seru, 2014, Gompers et al., 2005). Ultimately, post-merger human capital restructuring reflects a complex interplay between corporate strategy and individual decisions, shaped by both the matching and screening channels.

5.1.3 The role of newly hired inventors

Understanding the role of newly hired inventors in the combined entity offers novel insights into how firms restructure inventors beyond merging firms. In contrast to retained inventors, new hires bring fresh expertise and skills, which can address gaps left by turnover and complement the existing talent pool.

Table 7 show the role of matching channels. Inventors with less alignment between their patenting expertise and the acquirer's technological focus are more likely to be new hires than retained inventors, as indicated by the significant negative coefficients in Columns (5) and (6). This suggests that firms may seek to diversify their innovation capabilities post-merger by integrating inventors with broader expertise. Besides, the screening channel is more effective for the combined entity to hire highly productive talent from outside. As shown in Columns (5) and (6) of Table 8, more productive inventors pre-merger are more likely to be new hires.

Further evidence from Panel B of Table 9 reveals that for inventors whose expertise lies outside the combined entity's core business ($SameCore = 0$) or whose patents show little technological overlap with the combined entity ($CosineSimilarity = 0$), higher pre-merger productivity increases the likelihood of being new hires relative to retained inventors, shown by the significant positive coefficients of $Prod_{t-1}$ across all the specifications. This highlights the firm's preference for hiring highly productive inventors, particularly in peripheral areas.

Other inventor-specific characteristics also influence the likelihood of external hiring. Inventors who patent across multiple technology classes, have fewer years of patenting experience and smaller network sizes are more likely to be new hires than retained inventors.

These findings suggest a shift in hiring preferences within the merged entity. Inventors with expertise in non-core areas are more likely to be new hires than retained inventors, potentially serving as "glue" to integrate talent from the merging firms. Additionally, inventors with smaller networks and fewer years of patenting experience, yet higher pre-merger productivity, are also more likely to be hired than retained. This finding is consistent with Gehrke et al. (2021), which shows that post-merger firms tend to hire younger, but slightly better-skilled, rank-and-file employees. Another plausible explanation is that these new hires are focused on emerging technological areas that have recently gained importance.

This hiring strategy complements internal restructuring, where highly productive inventors in peripheral technological areas are less likely to remain post-merger. The influx of newly hired inventors supports the idea that M&As increase the marginal benefit of job switches for external inventors by creating new opportunities. This reduction in labor market frictions, in turn, enables the entry of high-potential, younger talent into the combined entity.

5.2 Drivers of innovation productivity increase for inventors moving across firms

While much of the existing literature has focused on inventors who remain with merging firms and their contributions to the merged entity's innovation outcomes, inventors who leave or join these firms following M&As are often overlooked. Evidence in Section 4 suggests that both groups — those who depart and those newly hired — experience a significant boost in their innovation productivity post-merger. Departed inventors increase their output in both patent counts and citation-weighted patents compared to their counterparts in control firms. Although newly hired inventors file fewer patents, they show a marked increase in citation-weighted patents after the merger. These findings suggest that the reallocation of innovative human capital extends beyond the merging firms and positively impacts the broader innovation labor market.

To better understand the factors driving innovation performance among departed and newly hired inventors, this section explores two plausible channels through a series of subsample tests: (1) labor market frictions and (2) employer-employee technology overlap.

5.2.1 Labor market frictions

A plausible explanation for the observed increase in innovation productivity among inventors moving across firms post-merger is that M&As reduce labor market frictions, making job transitions easier for these inventors. If this mechanism is indeed at play, I would expect inventors facing higher labor market frictions to benefit more from this restructuring process. To test this hypothesis, I use an inventor's pre-merger productivity as a proxy for the level of labor market frictions they face, under the assumption that more productive inventors, being more mobile, experience fewer labor market frictions than their less productive counterparts.

I classify inventors into two groups: highly productive inventors and others, based on their pre-merger innovation performance. Highly productive inventors are defined as those in the top quartile of citation-weighted patents (adjusted for filing year and technological class) filed up to one year before the deal announcement, within both the treatment and control samples of departed (or newly hired) inventors. Table 10 presents the results: Columns (1) to (4) for departed inventors, and Columns (5) to (8) for newly hired inventors.

[*Insert Table 10 here*]

The findings indicate that the post-merger boost in innovation productivity is predominately driven by inventors in the non-top performer group. Departed inventors in the less productive group show a significant 5.1% increase in patent counts and a 22% increase in citation-weighted patents, while less productive newly hired inventors experience a 20% rise in citation-weighted patents. These results support the hypothesis of reduced labor market frictions: lower-performing inventors likely face greater barriers in finding optimal job opportunities. M&As help alleviate these frictions, leading to significant productivity gains. In contrast, highly productive inventors do not exhibit notable post-merger productivity improvements, potentially because they already face fewer labor market frictions and have better access to suitable roles, even without the restructuring effects of M&As.

5.2.2 Employer-employee technology overlap

Having established that the post-merger increase in innovation productivity is driven by inventors facing higher labor market frictions, I now explore a specific mechanism through which M&As may alleviate these frictions: the technology overlap between inventors and their new employer firms. In other words, M&As may increase innovation productivity of inventors by reallocating them to firms where their patenting areas have a higher overlap.

To test this hypothesis, I calculate technological overlap using the cosine similarity of technology class vectors derived from patents filed by inventors and their post-merger employers, up to one year before the deal announcement. Columns (1) to (4) in Table 11 report results for the subsample of departed inventors whose technological overlap with their post-merger employers falls in the top quartile, compared to other inventors. These new employers include both public and private firms, as identified by the USPTO. Similarly, Columns (1) to (4) in Table 12 present results for the subsample of newly hired inventors with a top quartile technological overlap with their new employers (i.e., acquiring firms), compared to others.

[*Insert Table 11 here*]

[*Insert Table 12 here*]

The results show that departed inventors with a higher technological overlap with their new employer firms file 9.1% more patents and 9.5% more citation-weighted patents compared to their counterparts. For newly hired inventors, the increase in citation-weighted patents is observed in both high- and low-overlap subsamples, but is notably stronger among those with higher overlap, where newly hired inventors produce 24% more citation-weighted patents than their counterparts. In contrast, this effect is more than halved in the lower-overlap group. These findings strongly suggest that M&As reduce labor market frictions by reallocating inventors to firms where their expertise better aligns with the firm's innovation focus. This improved technology overlap appears to be a key mechanism driving the observed increases in post-merger innovation productivity for inventors who switch jobs.

Additionally, I provide corroborating evidence by examining the technological overlap of inventors with their pre-merger employer firms. Following a similar process to categorize inventors into subsamples based on higher versus lower technological overlap, Columns (5)–(8) in Table 11 present the results for departed inventors in relation to their pre-merger CRSP public firms (i.e., the merging firms in the treated or control samples). Columns (5)–(8) in Table 12 show the results for newly hired inventors in relation to their pre-merger assignees, which include both public and private firms identified by the USPTO.

The results for pre-merger inventor-firm technological overlap are less clear but still support the improved matching channel.Departed inventors with lower technological overlap at their pre-merger firms show a 3.1% increase in patent counts and a 13% rise in citation-weighted patents. In contrast, those with higher overlap see a greater increase in patent counts (6%) but a smaller gain in citation-weighted patents (8.7%). This suggests that inventors with a poorer fit at their pre-merger firms benefit more from restructuring, especially in terms of patent quality.

For newly hired inventors, I find those with a higher technological overlap with their pre-merger firms file fewer patents but produce 23% more citation-weighted patents. In contrast, inventors with lower overlap show no significant change in patent counts but see a 12% increase in citation-weighted patents. These findings suggest different channels driving innovation productivity gains for newly hired inventors. Firms successfully select inventors with strong pre-merger overlap, who produce higher-quality patents at the expense of quantity. Meanwhile, those with lower overlap still experience gains, indicating that the improved match channel is particularly relevant for this group.

Analyzing the productivity changes of both departed and newly hired inventors offers a comprehensive view of how M&As restructure innovative talent beyond the merging firms. Productivity gains are concentrated among non-top performers facing higher labor market frictions and those with greater technological overlap with their new employers. These findings are consistent with the notion that labor market frictions limit inventors' ability to freely allocate themselves to their most valuable roles. M&As reduce these frictions by expanding job opportunities for external inventors and lowering the marginal cost of job searching for those within the merging firms, leading to improved innovation performance for those switching jobs post-merger.

6 Conclusion

This paper examines the restructuring of innovative labor following M&As, exploring whether these transactions lead to a reallocation of inventors similar to that of real assets across firms. Using detailed inventor-level data, I track the evolution of the innovative workforce within the combined entity and assess how this restructuring affects the output of different inventor groups.

I find substantial turnover among target inventors post-merger, while acquirer inventors experience significantly lower departure rates. Despite this restructuring, the proportion of newly hired inventors and the overall size of inventor teams remain relatively unchanged compared to the pseudo-merging pairs. At the inventor level, I observe that post-merger, inventors in the combined entity file significantly more citation-weighted and high economic-valued patents. This effect is primarily driven by acquiring inventors who remain and by newly hired inventors, while target inventors who stay experience a notable decline in productivity. Departed inventors, particularly from the acquirer group, show substantial increases in innovation productivity.

The increased turnover among target firm inventors and productivity gains for both staying and departed inventors suggest that the inventor labor market frictions are economically important. M&As appear to reduce these frictions and reallocate inventors to more valuable uses.

Digging deeper into the economic mechanisms, the analysis shows that inventor restructuring in merging firms primarily supports the *matching channel*. Inventors whose technological expertise is less aligned with their employer's core focus are more likely to leave. In contrast, evidence for the screening channel is limited, as M&As do not ensure the retention of inventors with significantly higher pre-merger productivity. Retention of productive inventors is only effective when an inventor's expertise closely aligns with the merging firm or acquirer's core technologies. These results highlight fundamental differences between restructuring physical assets and human capital in M&As. Unlike the divestment of unproductive plants commonly seen in asset reallocation, highly productive inventors may still depart after a merger.

The analysis also reveals a shift in hiring preferences following M&As. Inventors with expertise in non-core technological areas and higher pre-merger productivity are more likely to be new hires than retained employees. This hiring strategy complements internal restructuring, as highly productive inventors in peripheral areas are less likely to stay. Additionally, new hires tend to have smaller networks and less patenting experience, supporting the idea that M&As facilitate the entry of high-potential, younger talent. By expanding job opportunities and reducing labor market frictions for external inventors, M&As help attract innovative talent that might otherwise face barriers in the labor market.

Analyzing post-merger productivity changes in inventors who switch jobs, along with their drivers, provides a comprehensive view of how M&As restructure human capital beyond the merging firms. The key findings that both departed and newly hired inventors see significant productivity increases highlight the role of reduced labor market frictions. Subsample analyses show that these gains are primarily driven by non-top performers and those with greater technological overlap with their new employers. This suggests M&As alleviate labor market frictions, particularly for lower-performing inventors. By reshaping or forming new firm structures, M&As "liberate" inventors who are previously constrained, allowing them to transition into roles better aligned with their patenting areas.

These findings highlight the significant economic impact of M&As on the restructuring and productivity of innovative labor, both within and beyond the combined entity. The results also carry important policy implications. M&As appear to reduce labor market frictions and improve the allocation of innovative talent. Policymakers could support smoother transitions by reducing mobility barriers, such as improving inventor-friendly non-compete agreements or intellectual property rights transfer protocols. Furthermore, promoting transparency in technological capabilities during mergers may help firms and inventors form better matches, further driving innovation and economic growth.

7 Figures and tables

Figure 1: Number of CRSP public M&As and percentage of innovative deals

The bars represent the total number of CRSP public M&A deals from 1984 to 2017 (left y-axis). The red bars indicate innovative deals where both acquirer and target firms have at least one inventor one year before the merger, while the blue bars represent all other CRSP public M&A deals. The yellow dotted line shows the ratio of innovative deals to all CRSP public deals during the sample period (right y-axis).

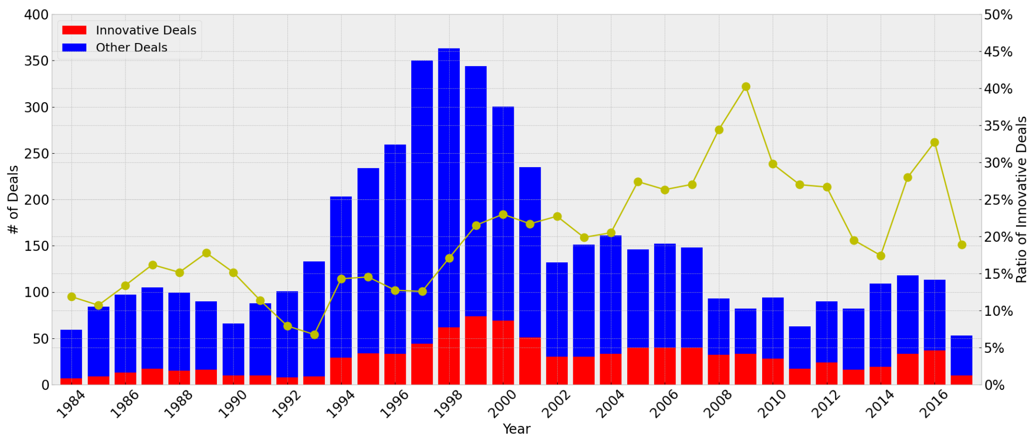


Figure 2: Number of innovative firms and non-innovative firms

The red bars show the number of innovative firms associated with at least one inventor, while the blue bars represent non-innovative firms with no inventor associations, over the sample period from 1984 to 2017. The yellow dotted line plots the percentage of innovative firms among all public firms with available information in CRSP and unique PERMNOs over time during the sample period.

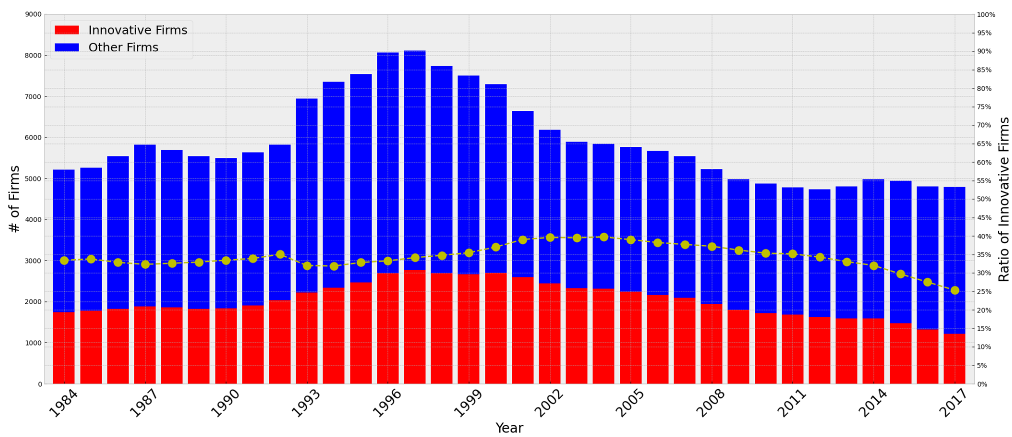
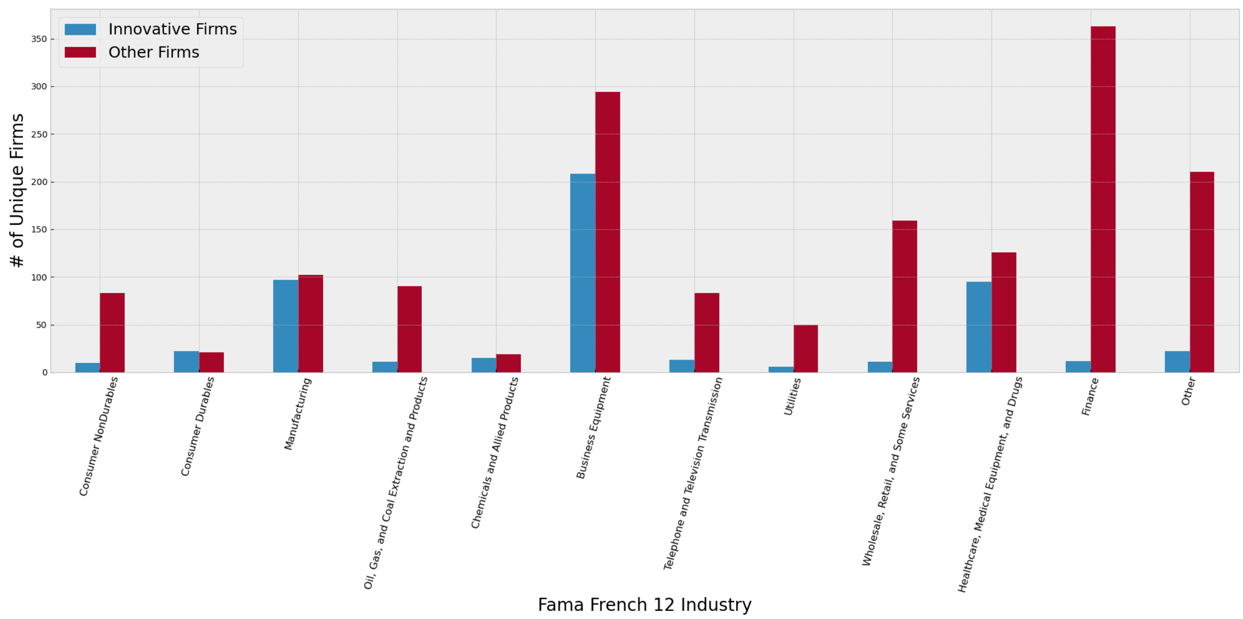
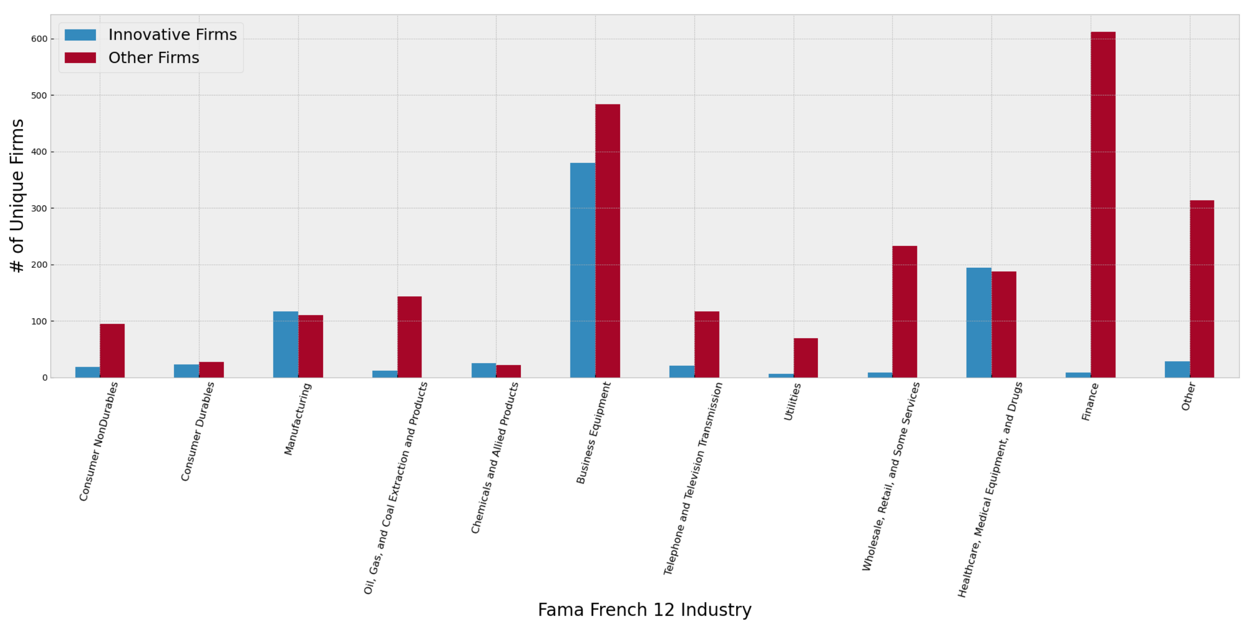


Figure 3: Industry distribution of innovative firms versus other firms

This figure shows the industry distribution of innovative merging firms compared to other merging firms across all deals during the sample period. I collect the merging firms' historical SIC codes from one year before the deal announcement and map them to the Fama-French 12 Industry Classification. Innovative firms are defined as those associated with at least one inventor one year before the deal announcement. Panel A displays the industry distribution of the unique number of innovative acquirers (blue bars) versus other acquirers (red bars), while Panel B presents the industry distribution of the unique number of innovative target firms (blue bars) versus other target firms (red bars).



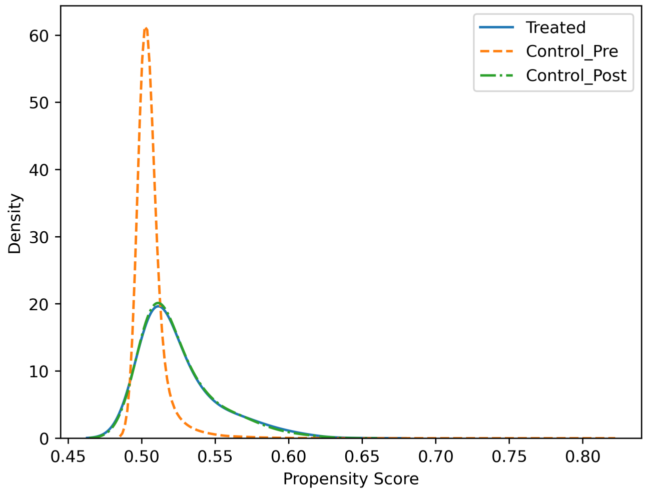
(a) Acquirer Firms



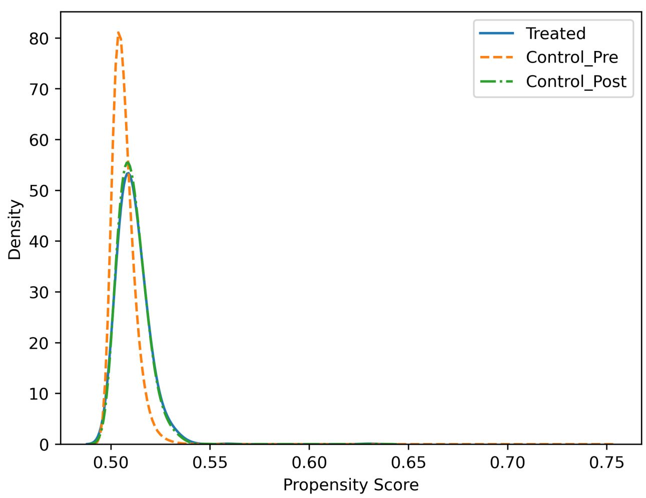
(b) Target firms

Figure 4: Density plots of propensity scores for merging (treated) and control firms

This figure plots the density of the propensity score of being involved in an acquisition for treated and control firms. The blue solid line represents the propensity score density for the treated (or merging) firms. The orange dashed line shows the control firms' density before implementing the propensity score matching technique, and the green dash-dotted line represents the control firms after applying the matching technique. Figure 1(a) displays the effects of matching for the acquirer firms, while Figure 1(b) shows the effects of matching for the target firms.



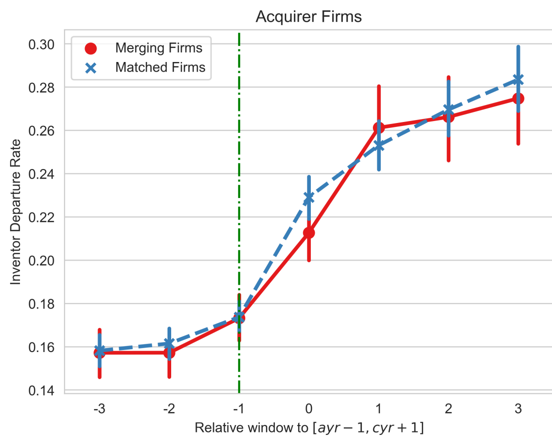
(a) Acquirer Firms



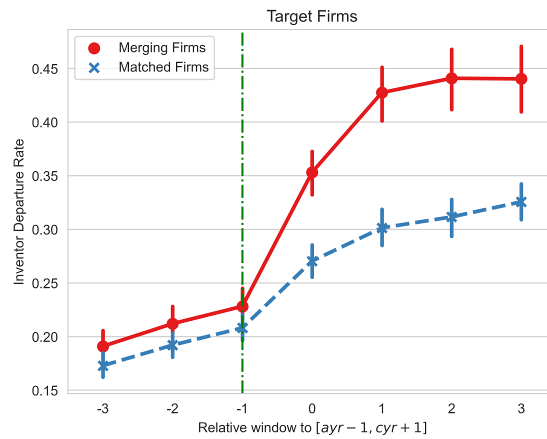
(b) Target Firms

Figure 5: Parallel trend analysis for inventor turnovers

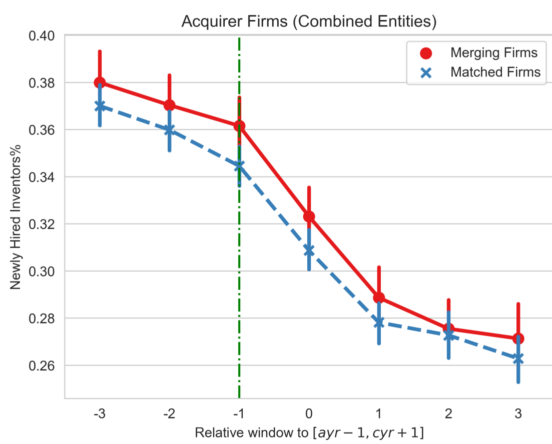
This figure plots the group mean and 95% confidence intervals for inventor turnver-related outcome variables in merging firms and their matched pseudo firms. The outcome variables are calculated over windows relative to the one used in the main analysis $[ary-1, cyr+1]$. Each window has the same length l as $[ary-1, cyr+1]$, which differs by deal. The rest of the windows are defined as rolling windows by shifting the window one year to the left (or to the right).



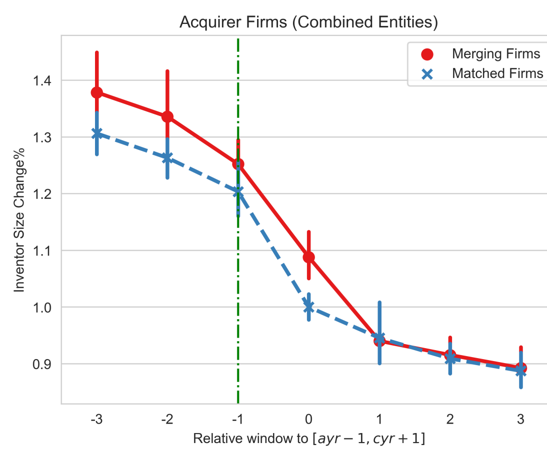
(a) AcqLeave%



(b) TarLeave%



(c) New%



(d) SizeChange%

Table 1: Summary statistics of innovative M&A deals

Panel A presents the summary statistics of deal-level characteristics for innovative M&A deals, and Panel B presents the summary statistics of firm-level characteristics for innovative M&A deals in one year before deal announcement year ($ayr - 1$). Total assets are reported in real terms relative to the year 2019. Asterisks next to each variable in Panel B denote the significance of the mean difference between innovative acquirers and innovative target for that variable (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Detailed variable definitions are provided in Appendix A.

Panel A: Deal Characteristics				
	Mean	*Median*	*Std*	*N*
Diversify	0.38	0.00	0.49	845
All Cash	0.38	0.00	0.49	845
All Stock	0.33	0.00	0.47	845
Relative Size	0.30	0.13	0.95	840

Panel B: Firm Characteristics at $ayr - 1$								
	Acquirer Firms				**Target Firms**			
	Mean	*Median*	*Std*	*N*	*Mean*	*Median*	*Std*	*N*
Log(1+Inventors) ***	4.39	4.26	2.09	845	2.36	2.08	1.31	845
Log(1+AdjPatents) ***	4.09	3.80	2.32	845	2.41	2.21	1.51	845
Log(1+AdjPatents_5Y) ***	3.31	3.19	2.04	845	1.66	1.39	1.24	845
ROA ***	0.11	0.14	0.23	844	-0.01	0.09	0.31	844
Leverage	0.18	0.16	0.16	845	0.18	0.10	0.25	845
Asset Tangibility **	0.20	0.16	0.15	844	0.18	0.13	0.16	844
OCF/Asset ***	0.11	0.14	0.23	844	-0.01	0.09	0.31	844
Cash Holding/Asset ***	0.22	0.15	0.21	845	0.30	0.23	0.26	845
R&D/Asset ***	0.09	0.06	0.15	845	0.14	0.09	0.17	845
Log(TotalAssets)***	8.07	8.03	2.20	845	5.78	5.60	1.90	845
M/B	4.61	2.99	14.69	845	3.59	2.25	11.46	845
Tobin's Q **	2.82	2.03	4.11	845	2.42	1.73	2.39	845
Log(Spread)	0.04	0.03	0.02	845	0.06	0.05	0.14	843

Table 2: Summary statistics of inventor samples

This table presents the summary statistics of the inventor sample. Panel A summarizes the full inventor sample, which consists of all inventors impacted by the merger. That is, they are either associated with merging firms one year before the deal announcement date or one year after the deal completion date. Among full inventor sample, Panel B summarizes selected inventor sample where inventors have to file at least one patent both before and after the merger. Alternatively, Panel C summarizes the other inventors that are in the full inventor sample. Asterisks after each variable in Panel A denote the significance of mean difference between selected inventors and other inventors for this variable (* $(p < 0.1)$, **$(p < 0.05)$, ***$(p < 0.01)$.

	Mean	*Median*	*Std*	*N*
Panel A: Full Inventor Sample				
Number of Associated Assignees ***	2.45	2.00	1.77	296302
Active Years ***	15.95	14.00	10.00	296302
Number of Patents (Raw) ***	14.62	7.00	27.21	296302
Average Citations per Patent ***	17.80	7.67	41.13	296302
Number of Patents (Adjusted) ***	9.57	4.76	16.96	296302
Citation(Adjusted)-weighted Patents ***	19.35	4.87	290.02	296302
Real Value of Patents ($million) ***	159.94	42.34	467.09	296302
Number of High Value Patents (top 15%) ***	2.12	0.00	6.13	296302
Panel B: Selected Inventor Sample				
Number of Associated Assignees	2.69	2.00	1.86	230388
Active Years	18.25	17.00	9.68	230388
Number of Patents (Raw)	16.82	9.00	29.53	230388
Average Citations per Patent	18.57	8.50	41.54	230388
Number of Patents (Adjusted)	11.01	5.81	18.44	230388
Citation(Adjusted)-weighted Patents	22.65	6.12	327.81	230388
Real Value of Patents ($million)	183.89	51.02	513.63	230388
Number of High Value Patents (top 15%)	2.43	1.00	6.76	230388
Panel C: Other Inventor Sample				
Number of Associated Assignees	1.60	1.00	0.97	65914
Active Years	7.92	6.00	6.21	65914
Number of Patents (Raw)	6.93	4.00	14.26	65914
Average Citations per Patent	15.14	5.00	39.56	65914
Number of Patents (Adjusted)	4.53	2.48	8.52	65914
Citation(Adjusted)-weighted Patents	7.82	2.13	48.33	65914
Real Value of Patents ($million)	76.21	23.65	222.76	65914
Number of High Value Patents (top 15%)	1.02	0.00	2.72	65914

Table 3: Propensity score matching of acquirer and target firms

This table reports the results of propensity score matching for acquirer firms (Panel A) and target firms (Panel B). It lists the covariates used in the Probit regression to estimate the propensity score of being an innovative acquirer (target) firm. Column (1) presents the estimation coefficients from the Probit regression, while Column (2) shows the mean variables for acquirer (or target) firms, as in Panel B of Table 1. Columns (3) and (4) display the mean variables for candidate firms and the mean differences between treated and candidate control firms before matching. Columns (5) and (6) present the same information after matching. Standard errors are in parentheses in Column (1), and t-statistics are in parentheses in Columns (4) and (6). P-values are indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

			Before PSM		**After PSM**	
Covariates	Probit	Treated	Control	Diff	Control	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Acquirer Firms						
Log(1+Inventors)	0.09***	4.39	2.49	1.90***	4.25	0.14
	(0.013)			(26.31)		(1.53)
Log(1+AdjPatents)		4.09	1.73	1.65***	4.05	0.04
				(21.56)		(0.44)
Log(1+AdjPatents_5Y)		3.31	1.65	1.66***	3.21	0.10
				(23.58)		(1.11)
ROA	1.68***	0.11	-0.01	0.12***	0.12	-0.01
	(0.63)			(14.46)		(-0.75)
Leverage	-0.35***	0.18	0.20	-0.02***	0.19	-0.01
	(0.10)			(-2.88)		(-1.00)
Asset Tangibility	-0.83***	0.20	0.23	-0.03***	0.20	-0.01
	(0.14)			(-5.70)		(-1.22)
OCF-to-Asset Ratio	-1.47**	0.11	-0.01	0.11***	0.12	-0.01
	(0.62)			(13.26)		(-0.87)
R&D Intensity	0.33***	0.09	0.11	-0.02***	0.07	0.01***
	(0.09)			(-3.62)		(2.82)
Cash Ratio	-0.07	0.22	0.25	-0.03***	0.21	0.01
	(0.09)			(-4.35)		(1.23)
Log(TotalAssets)	0.17***	8.07	5.99	2.02***	8.04	0.03
	(0.01)			(26.04)		(0.34)
M/B		4.61	1.10	3.48*	4.48	0.12
				(1.82)		(0.09)
Tobin's Q	0.01**	2.82	2.52	0.27*	2.86	-0.04
	(0.00)			(1.79)		(-0.16)
Log(Spread)	0.53*	0.04	0.05	-0.01***	0.04	0.00**
	(0.31)			(-15.19)		(2.21)
Industry FE	Yes					
Deal Announcement Year FE	Yes					
Observations	50778					
Pseudo R^2	0.16					
Panel B: Target Firms						
Log(1+Inventors)	-0.29***	2.36	2.48	-0.12***	2.38	-0.02
	(0.03)			(-2.65)		(-0.37)
Log(1+AdjPatents)		2.41	2.36	0.06	2.37	0.05
				(1.07)		(0.67)
Log(1+AdjPatents_5Y)	0.26***	1.66	1.65	0.02	1.69	-0.02
	(0.03)			(0.39)		(-0.40)
ROA	0.44	-0.01	-0.01	-0.00	-0.02	0.01
	(0.59)			(-0.17)		(0.50)
Leverage	0.04	0.18	0.20	-0.02***	0.17	0.01
	(0.06)			(-2.73)		(0.54)
Asset Tangibility	-0.42***	0.18	0.23	-0.05***	0.18	0.00
	(0.12)			(-8.60)		(0.47)
OCF-to-Asset Ratio	-0.18	-0.01	-0.01	-0.00	-0.02	0.01
	(0.59)			(-0.21)		(0.49)
R&D Intensity	0.51***	0.14	0.11	0.03***	0.13	0.01
	(0.08)			(5.41)		(0.79)
Cash Ratio	0.20***	0.30	0.25	0.05***	0.31	-0.01
	(0.08)			(5.18)		(-0.94)
Log(TotalAssets)	0.05***	5.78	5.95	-0.17**	5.79	-0.01
	(0.01)			(-2.53)		(-0.06)
M/B		3.59	1.12	2.47	1.89	1.70
				(1.31)		(1.45)
Tobin's Q	-0.02***	2.42	2.53	-0.11	2.35	0.07
	(0.010)			(-1.27)		(0.80)
Log(Spread)	0.41**	0.06	0.05	0.01	0.05	0.00
	(0.20)			(1.22)		(0.91)
Industry FE	Yes					
Deal Announcement Year FE	Yes					
Observations	50839					
Pseudo R^2	0.06					

Table 4: Inventor restructuring around M&A

This table presents the results for inventor restructuring around M&As. The sample includes innovative deal and control samples using propensity score matching. Columns (1) and (3) (Columns (2) and (4) report the results of the first (second) DiD frameworks below:

$$y_{i,t} = \alpha_s + \alpha_{t,ind} + \beta_1 I(Post) + \beta_2 I(M\&A) + \beta_3 I(M\&A) \times I(Post) + \gamma X_{i,t-1} + e_{i,m,t},$$
$$y_{i,t} = \alpha_m + \alpha_{t,ind} + \beta_1 I(Post) + \beta_3 I(M\&A) \times I(Post) + e_{i,m,t}.$$

Here, $y_{i,t}$ represents a set of variables indicating the mobility of different groups of inventors in firm i (expressed as percentage) examined within the $[ayr-1, cyr+1]$ window. Panel A examines the turnover rates of target and acquirer inventors, where the dependent variable is the departure rate of acquirer (target) inventors. Panel B examines changes in the inventor teams by studying the percentage of new inventors in the combined entity after the merger and the percentage change in the inventor team size within the $[ayr-1, cyr+1]$ window. $I(Post)$ is a dummy variable equal to one if the inventor turnover is calculated within the $[ayr-1, cyr+1]$ window, and zero if calculated within a window of the same length ending in year $ayr-1$. $I(M\&A)$ is an indicator variable equal to one if the firm is involved in the M&As, and zero otherwise. $X_{i,t-1}$ includes all the covariates in year $ayr-1$ used in the balance check analysis in Table 3. $\alpha_{t,ind}$ is the Year × Industry FE, where the year is one year before deal announcement year, and industry is defined by SIC-2 digits. α_s represents the stacked matching group fixed effect, and α_m represents the deal-firm fixed effect. The standard errors are clustered at the stacked matching group level and are displayed in the parentheses in the first specification and at the deal-firm level in the second. p-values are indicated by * (p<0.10), ** (p<0.05), and *** (p<0.01).

	AcqLeave%		TarLeave%	
	(1)	(2)	(3)	(4)
Panel A: Acquirer and target inventor turnovers				
$I(Post)$	-0.021	-0.019	0.013	0.003
	(0.026)	(0.027)	(0.051)	(0.053)
$I(M\&A)$	0.006		0.017	
	(0.0073)		(0.011)	
$I(Post) \times I(M\&A)$	-0.023**	-0.014*	0.056***	0.059***
	(0.0093)	(0.0080)	(0.015)	(0.015)
Controls	Yes	No	Yes	No
Stacked Group FE	Yes	No	Yes	No
$Deal - Firm\ FE$	No	Yes	No	Yes
$Year \times IndustryFE$	Yes	Yes	Yes	Yes
Observations	4333	4066	4103	3684
R^2	0.427	0.778	0.444	0.713
Panel B: The change of the inventor teams				
	New%		SizeChange%	
	(1)	(2)	(3)	(4)
$I(Post)$	-0.003	-0.001	0.016	0.088
	(0.023)	(0.025)	(0.11)	(0.11)
$I(M\&A)$	0.010		0.038**	
	(0.0061)		(0.019)	
$I(Post) \times I(M\&A)$	-0.001	-0.002	0.039	0.021
	(0.0077)	(0.0071)	(0.027)	(0.027)
Controls	Yes	No	Yes	No
Stacked Group FE	Yes	No	Yes	No
$Year \times IndustryFE$	Yes	Yes	Yes	Yes
$Deal - Firm\ FE$	No	Yes	No	Yes
Observations	4326	4056	4333	4066
R^2	0.598	0.813	0.576	0.774

Table 5: Productivity change of inventors in the combined entity around M&A

This table examines the productivity change of inventors that stay with combined entity one year after deal completion relative to inventors with the same labor outcomes in the corresponding control firms. It includes four groups: (1) staying inventors from acquirer firms, (2) staying inventors from target firms, (3) newly hired inventors, and (4) all inventors from groups (1) through (3). The results are reported from the following Poisson DiD regression:

$$E[y_{j,m}|\mathbf{x}] = e^{\mathbf{x}\beta} = e^{\beta_0+\beta_1 I(Post)+\beta_2 I(M\&A)\times I(Post)+\alpha_t+\alpha_{j,m}+e_{j,m,t}}$$

Innovation performance is measured by: (1) the number of adjusted granted patents, (2) the number adjusted of citations-weighted patents, and (3) the sum of real economic value for patents, as per Kogan et al. (2017), filed by the inventor j year in year t. Note that the real value measure is not provided for newly hired inventors because some of these inventors may come from private firms, leading to missing values. if an inventor does not file any patent in a given year, the patent-based measures are assigned a value of zero. Year FE and Deal $\times$ Inventor FE are included. The standard errors are clustered at the Deal $\times$ Inventor level and are shown in parentheses. p-value indicated by * $(p < 0.10)$, ** $(p < 0.05)$, and *** $(p < 0.01)$.

Panel A: Staying inventors						
	Acquirer			Target		
	(1) AdjPatent	(2) AdjCPatent	(3) RealValue	(4) AdjPatent	(5) AdjCPatent	(6) RealValue
$I(Post)$	-0.032***	-0.12***	-0.14***	0.022**	-0.023	-0.044**
	(0.003)	(0.021)	(0.01)	(0.01)	(0.022)	(0.020)
$I(Post) \times I(M\&A)$	0.062***	0.23***	0.022**	-0.26***	-0.26***	-0.30***
	(0.004)	(0.030)	(0.009)	(0.018)	(0.042)	(0.046)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal × Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6632880	6248959	5408784	953050	908147	756310

Panel B: Other/All inventors in the combined entity					
	Newly Hired		All Inventors		
	(1) AdjPatent	(2) AdjCPatent	(3) AdjPatent	(4) AdjCPatent	(5) RealValue
$I(Post)$	0.13***	0.17***	-0.0021	-0.064***	-0.014
	(0.008)	(0.031)	(0.003)	(0.019)	(0.010)
$I(Post) \times I(M\&A)$	-0.047***	0.13***	0.045***	0.21***	0.025***
	(0.011)	(0.048)	(0.004)	(0.027)	(0.009)
Year FE	Yes	Yes	Yes	Yes	Yes
Deal × Inventor FE	Yes	Yes	Yes	Yes	Yes
N	1075871	1019726	7728834	7288707	6268156

Table 6: Productivity change of departed inventors around M&A

This table examines the productivity change of departed inventors from merging firms after deal completion, which includes (1) inventors leaving acquirer firms, (2) inventors leaving target firms, and (3) all departed inventors. The results are reported from the same Poisson regression as in Equation (6). Similarly, the matched inventor sample consists of departed acquirer (target) inventors from the matched acquirer (target) firms constructed in Section 3. if an inventor does not file any patent in a given year, the patent-based measures are assigned a value of zero. Year FE and Deal $\times$ Inventor FE are included. The standard errors are clustered at the Deal $\times$ Inventor level and are shown in parentheses. p-value indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

	Acquirer Departed		Target Departed		All Departed	
	(1) AdjPatent	(2) AdjCPatent	(3) AdjPatent	(4) AdjCPatent	(5) AdjPatent	(6) AdjCPatent
$I(Post)$	0.097***	0.16***	0.17***	0.18***	0.10***	0.16***
	(0.007)	(0.025)	(0.018)	(0.050)	(0.006)	(0.022)
$I(Post) \times I(M\&A)$	0.040***	0.079***	-0.065**	0.038	0.029***	0.073***
	(0.010)	(0.027)	(0.029)	(0.064)	(0.009)	(0.025)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal $\times$ *Inventor FE*	Yes	Yes	Yes	Yes	Yes	Yes
N	1260500	1192038	219902	208533	1480402	1400571

Table 7: The impact of matching on inventors' post-merger labor outcomes

This table examines the impact of matching on inventors' post-merger labor outcomes using a linear probability model as follows:

$$y_{i,j,d,t} = \alpha_d + \alpha_t + \beta_1 Match_{i,j,t-1} + \gamma X_{i,j,t-1} + e_{i,j,t}$$

Columns (1) to (4) show the results for inventors in acquirer or target firms. $y_{i,j,d,t}$ equals one if inventor j leaves the merging firm i one year after the deal completion date at time t, and zero otherwise. Columns (7) and (8) show the results for all staying inventors in the combined entity one year after deal completion. $y_{i,j,d,t}$ is a dummy variable equal to one if the inventor j is a newly hired inventor and zero if she is a staying inventor from the merging firms. α_d is the deal fixed effect, and α_t is the pre-announcement year fixed effect in $ayr - 1$. The independent variable is the inventor-firm technological overlap, $Match_{i,j,t-1}$, or the overlap between target inventors and acquirers, $Match_{Acq_i,j,t-1}$, measured by (1) *SameCore* and (2)*CosineSimilarity*. Other control variables are defined in the Appendix A. The standard errors are clustered at the deal level and are shown in parentheses. p-value indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

	Acquirer inventors		Target inventors				Newly hired inventors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Leave	Leave	Leave	Leave	Leave	Leave	New	New
SameCore	-0.018***		-0.015**				-0.062***	
	(0.004)		(0.008)				(0.004)	
CosineSim		-0.023***		-0.012				-0.130***
		(0.007)		(0.021)				(0.007)
SameCore_{Acq}					-0.010			
					(0.013)			
CosineSim_{Acq}						-0.022		
						(0.024)		
HHI	-0.035***	-0.036***	-0.022**	-0.023***	-0.023***	-0.023***	-0.032***	-0.035***
	(0.003)	(0.003)	(0.009)	(0.008)	(0.009)	(0.009)	(0.002)	(0.002)
Log(1+Active Years)	0.030***	0.031***	0.046***	0.046***	0.046***	0.046***	0.019***	0.016***
	(0.004)	(0.004)	(0.012)	(0.012)	(0.011)	(0.011)	(0.004)	(0.004)
Log(1+Network Size)	-0.006***	-0.005***	-0.008	-0.008	-0.009	-0.008	-0.029***	-0.025***
	(0.001)	(0.001)	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)
N	323075	323075	16243	16243	16243	16243	335868	335868
R^2	0.052	0.052	0.175	0.175	0.175	0.175	0.100	0.105

Table 8: The impact of screening on inventors' post-merger labor outcomes

This table examines the impact of matching on inventors' post-merger labor outcomes using a linear probability model as follows:

$$y_{i,j,d,t} = \alpha_d + \alpha_t + \beta_1 Prod_{i,t-1} + \gamma X_{i,j,t-1} + e_{i,j,t}$$

Columns (1) to (4) show the results for inventors in acquirer or target firms. $y_{i,j,d,t}$ equals one if inventor j leaves the merging firm i one year after the deal completion date at time t, and zero otherwise. Columns (5) and (6) show the results for all staying inventors in the combined entity one year after deal completion. $y_{i,j,d,t}$ is a dummy variable equal to one if the inventor j is a newly hired inventor and zero if she is a staying inventor from the merging firms. α_d is the deal fixed effect, and α_t is the year fixed effect in $ayr - 1$. $Prod_{i,t-1}$ measures the pre-merger productivity of inventor i up till $t-1$ using (1) log of one plus the number of patents filed in year t (adjusted for filing year and technological class); (2) log of one plus the number of citations received by patents filed in year t (adjusted for filing year and technological class). Other control variables are defined in the Appendix A. The standard errors are clustered at the deal level and are shown in parentheses. p-value indicated by * $(p < 0.10)$, ** $(p < 0.05)$, and *** $(p < 0.01)$.

	Acquirer inventors		Target inventors		Newly hired inventors	
	(1)	(2)	(3)	(4)	(5)	(6)
	Leave	Leave	Leave	Leave	New	New
Ln(1+AdjPatent)	0.012***		0.022***		0.066***	
	(0.002)		(0.007)		(0.002)	
Ln(1+AdjCPatent)		0.007***		0.005		0.033***
		(0.001)		(0.005)		(0.002)
HHI	-0.032***	-0.034***	-0.018**	-0.023**	-0.017***	-0.029***
	(0.002)	(0.003)	(0.009)	(0.009)	(0.002)	(0.002)
Log(1+Active Years)	0.025***	0.028***	0.033**	0.043***	-0.011**	0.004
	(0.005)	(0.004)	(0.013)	(0.013)	(0.004)	(0.004)
Log(1+Network Size)	-0.009***	-0.009***	-0.016***	-0.011**	-0.050***	-0.044***
	(0.001)	(0.001)	(0.005)	(0.006)	(0.002)	(0.002)
N	323075	323075	16243	16243	335868	335868
R^2	0.052	0.052	0.175	0.175	0.099	0.095

Table 9: The impact of interaction between matching and screening on inventors' post-merger labor outcomes

This table examines the impact of the interaction between matching and screening channels on inventors' post-merger labor outcomes using a linear probability model as follows:

$$y_{i,j,t} = \alpha_d + \alpha_t + \beta_1 Match_{i,j,t-1} \times Prod_{i,t-1} + \beta_2 Match_{i,j,t-1} + \beta_3 Prod_{i,t-1} + \gamma X_{i,j,t-1} + e_{i,j,t}$$

The specifications and variables are the same as in Table 7 and Table 8. Panel A shows the cross-sectional patterns for target inventors, and Panel B shows the results for acquirer inventors and inventors in the combined entity after the deal completion (i.e., staying inventors and newly hired inventors).

Panel A: Inventors from target firms								
	Match with target firms				Match with acquirer firms			
Match$_{i,j,t-1}$=	SameCore	CosineSim	SameCore	CosineSim	SameCore	CosineSim	SameCore	CosineSim
Prod$_{t-1}$ =	Ln(1+AdjPatent)		Ln(1+AdjCPatent)		Ln(1+AdjPatent)		Ln(1+AdjCPatent)	
	Leave (1)	Leave (2)	Leave (3)	Leave (4)	Leave (5)	Leave (6)	Leave (7)	Leave (8)
Match$_{i,j,t-1}$	0.021	0.050*	0.014	0.045*	0.038**	0.035	0.034*	0.033
	(0.015)	(0.027)	(0.013)	(0.024)	(0.018)	(0.025)	(0.018)	(0.025)
Prod$_{t-1}$	0.038***	0.059***	0.016***	0.034***	0.037***	0.046***	0.017***	0.026***
	(0.010)	(0.014)	(0.006)	(0.009)	(0.008)	(0.010)	(0.006)	(0.007)
Match$_{i,j,t-1}$× Prod$_{t-1}$	-0.026***	-0.052***	-0.018***	-0.042***	-0.034***	-0.045***	-0.027***	-0.038***
	(0.010)	(0.016)	(0.007)	(0.011)	(0.010)	(0.014)	(0.007)	(0.009)
HHI	-0.015*	-0.014	-0.020**	-0.019**	-0.016*	-0.015*	-0.020**	-0.020**
	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
Log(1+Active Years)	0.033**	0.032**	0.043***	0.043***	0.033**	0.033**	0.042***	0.042***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Log(1+Network Size)	-0.016***	-0.016***	-0.011*	-0.011*	-0.016***	-0.016***	-0.011**	-0.011**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	16243	16243	16243	16243	16243	16243	16243	16243
R^2	0.177	0.177	0.176	0.176	0.177	0.177	0.176	0.176

Panel B: Inventors from acquirer firms/in the combined entity								
	Acquirer inventors				Inventors in the combined entity			
Match$_{i,j,t-1}$=	SameCore	CosineSim	SameCore	CosineSim	SameCore	CosineSim	SameCore	CosineSim
Prod$_{t-1}$ =	Ln(1+AdjPatent)		Ln(1+AdjCPatent)		Ln(1+AdjPatent)		Ln(1+AdjCPatent)	
	Leave (1)	Leave (2)	Leave (3)	Leave (4)	new (5)	new (6)	new (7)	new (8)
Match$_{i,j,t-1}$	0.008*	0.027***	-0.010**	0.000	-0.054***	-0.101***	-0.059***	-0.118***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)
Prod$_{t-1}$	0.021***	0.036***	0.010***	0.018***	0.065***	0.082***	0.033***	0.042***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Match$_{i,j,t-1}$× Prod$_{t-1}$	-0.018***	-0.039***	-0.005***	-0.017***	-0.003	-0.024***	-0.001	-0.012***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)
HHI	-0.031***	-0.030***	-0.033***	-0.033***	-0.015***	-0.015***	-0.026***	-0.027***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Log(1+Active Years)	0.025***	0.024***	0.026***	0.026***	-0.015***	-0.020***	-0.001	-0.006
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log(1+Network Size)	-0.009***	-0.009***	-0.008***	-0.008***	-0.047***	-0.043***	-0.042***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
N	323075	323075	323075	323075	335868	335868	335868	335868
R^2	0.053	0.053	0.052	0.052	0.110	0.115	0.106	0.111

Table 10: Subsample tests for productivity change of inventors moving across firms: highly productive inventors

This table conducts heterogeneity tests on the productivity changes of inventors who move across firms after deal completion, separating the observations into highly productive inventors and others based on their pre-merger productivity. Columns (1) to (4) report the results for departed inventors, while Columns (5) to (8) report the results for newly hired inventors. Highly productive inventors are identified as those ranking in the top quartile of citation-weighted patents (adjusted for filing year and technological class) filed up to one year before the deal announcement, among all departed or newly hired inventors in both treated and control samples. Odd-numbered columns report results for the highly productive inventor subsample, while even-numbered columns present results for the other inventor group. The specification is the same as Table 6. p-value indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

	Departed Inventors				Newly Hired Inventors			
	AdjPatent		AdjCPatent		AdjPatent		AdjCPatent	
	Top 25th (1)	Others (2)	Top 25th (3)	Others (4)	Top 25th (5)	Others (6)	Top 25th (7)	Others (8)
$I(Post)$	0.056***	0.17***	-0.0070	0.48***	0.068***	0.21***	0.029	0.55***
	(0.010)	(0.0079)	(0.033)	(0.024)	(0.013)	(0.0089)	(0.041)	(0.038)
$I(Post) \times I(M\&A)$	-0.015	0.051***	-0.035	0.22***	-0.098***	-0.016	0.012	0.20***
	(0.016)	(0.010)	(0.036)	(0.030)	(0.018)	(0.010)	(0.076)	(0.047)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal $\times$ *Inventor FE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	372055	1102039	364578	1030915	263723	805428	258769	755389

Table 11: Subsample tests for productivity change of departed inventors: technological overlap

This table conducts heterogeneity tests on the productivity changes of all departed inventors by separating the observations based on the degree of employer-employee technological overlap measured in the pre-merger period. Technological overlap is calculated using the cosine similarity of technology classification vectors derived from patents filed by a departing inventor (from either a merging firm or a matched firm) and their post-merger (pre-merger) employer, up to one year before the deal announcement. Columns (1) to (4) report results for the subsample of departed inventors whose technological overlap with their post-merger employers falls in the top quartile, compared to other inventors. These post-merger employers include both public and private firms, as identified by the USPTO. Columns (5) to (8) present results for departed inventors in relation to their pre-merger CRSP public firms (i.e., the merging firms in the treated or control samples). The classification of subsamples based on technological overlap follows the same methodology as in the previous columns. The specification is the same as in Table 6. p-value indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

	Post-merger Assignees				Pre-merger Assignees (Public Firms)			
	AdjPatent		AdjCPatent		AdjPatent		AdjCPatent	
	Top 25th (1)	Others (2)	Top 25th (3)	Others (4)	Top 25th (5)	Others (6)	Top 25th (7)	Others (8)
$I(Post)$	0.037***	0.12***	0.17***	0.14***	0.093***	0.10***	0.14***	0.15***
	(0.010)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
$I(Post) \times I(M\&A)$	0.091***	0.014	0.095**	0.039	0.060***	0.031**	0.087*	0.13***
	(0.000)	(0.201)	(0.033)	(0.166)	(0.000)	(0.012)	(0.079)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal × Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	325335	923829	309369	874383	382919	1091154	362469	1032894

Table 12: Subsample tests for productivity change of newly hired inventors: technological overlap

This table conducts heterogeneity tests on the productivity changes of newly hired inventors by separating the observations based on the degree of employer-employee technological overlap in the pre-merger period. The overlap is calculated using the cosine similarity of technology classification vectors from patents filed by the inventor and their post-merger (pre-merger) employer up to one year before the deal announcement date. Columns (1) to (4) report the results for newly hired inventors whose technological overlap with their post-merger employers falls in the top quartile, compared to other inventors. Columns (5) to (8) present results for newly hired inventors in relation to their pre-merger assignees, which include both public and private firms identified by the USPTO. The classification of subsamples based on technological overlap follows the same methodology as in the previous columns. The specification is the same as in Table 6. p-value indicated by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

	Post-merger Assignees (Public Firms)				Pre-merger Assignees			
	AdjPatent		AdjCPatent		AdjPatent		AdjCPatent	
	Top 25th (1)	Others (2)	Top 25th (3)	Others (4)	Top 25th (5)	Others (6)	Top 25th (7)	Others (8)
$I(Post)$	0.14***	0.11***	0.068	0.20***	0.14***	0.095***	-0.0097	0.22***
	(0.000)	(0.000)	(0.208)	(0.000)	(0.000)	(0.000)	(0.860)	(0.000)
$I(Post) \times I(M\&A)$	-0.0076	-0.014	0.24**	0.11**	-0.053***	0.0056	0.23**	0.12**
	(0.667)	(0.199)	(0.012)	(0.029)	(0.007)	(0.598)	(0.014)	(0.014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal × Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	274321	794439	262220	751547	280389	782750	268311	740585

Appendix A   Variable definitions

Variable	Definitions
A. Deal characteristics	
Diversify	Dummy equals to zero if the acquirer and the target firm are in different industries (2-digit SIC), and zero otherwise
All Cash	Dummy equals to one if the deal is paid 100% by cash, and zero otherwise
All Stock	Dummy equals to one if the deal is paid 100% by stock, and zero otherwise
Relative Size	The ratio of deal value to an acquirer's market value of assets
B. Firm characteristics	
Market value of Asset	Defined as liability (LT)) - balance sheet deferred taxes and investment tax credit (TXDITC) + preferred stock + market equity (CSHO $\times$ PRCC_F) in $ayr-1$
Market Capitalization	Multiplication of the current stock price of the firm by the total number of outstanding shares (CSHO $\times$ PRCC_F)
Tobin's Q	The ratio of market value of asset to the book value of asset in $ayr-1$
ROA	The ratio of net income (NI) to the book value of asset in $ayr-1$
OCF-to-Asset Ratio	The ratio of Operating Cash Flow (OCF) to the book value of asset, where OCF = Sales - COGS - XSGA - WCAPCH at $ayr-1$
Cash Holdings-to-Asset Ratio	The ratio of cash (CHE) to book value of assets (AT) in $ayr-1$
Leverage	The ratio of total book debt (DLTT + DLC) to the book value of assets in $ayr-1$
R&D-to-Asset Ratio	The ratio of R&D expenditure (XRD) to the book value of assets in $ayr-1$
Log(Spread)	Natural log of Bid-Ask Spread Spread, defined as annual mean value of ratio (Ask or High (ASKHIt) - Bid or Low (BIDLOt))/Ask or High(ASKHIt)
Log(1+Inventors)	Natural log of one plus the number of inventors that are associated with the firm one year before the announcement date
Log(1+AdjPatents)	Natural log of one plus the number of granted patents the firm has filed up till one year before the deal announcement year $ayr-1$, adjusted for the technology classification and application year
Log(1+AdjPatents_5Y)	Natural log of one plus the number of granted patents the firm has filed in the recent 5 years ending one year prior to the deal announcement date, adjusted for the technology classification and application year

Variable	Definitions
C. Innovation variables	
Number of Patents	The number of eventually granted patents applied by an inventor (or a firm) in year t, adjusted for the technology classification and application year
Citation-weighted Patents	The number of scaled citations-weighted (and eventually granted) patent applied by an inventor (or a firm) in year t, where the citation is adjusted for the technology classification and application year
Real value of Patents	Value of innovation(ξ) deflated to 1982 (million) dollars using the CPI from Kogan et al. (2017)
Firm (inventor) core business	Patent technology class in which the firm (inventor) has the highest number of patents before $ayr - 1$
Cosine similarity score	The cosine similarity between the firm's class-based innovation vector and the inventor's class-based innovation vector, where the firm's (inventor's) innovation vector is the sum of all the innovation vectors of each patent that belongs to the focal firm(inventor)
D. Inventor characteristics	
Pre-merger productivity	Natural log of one plus the number of granted patents (or scaled citations-weighted patent) the inventor has filed till one year before deal announcement year
Log(1+Network size)	The natural logarithm of one plus the number of unique inventors that can be linked with the focal inventor through collaboration within two teams
Inventor specialization	The specialization degree of a given inventor is calculated as one minus the Herfindahl index of the three-digit technology class-share of granted patents filed by the focal inventor till one year before deal announcement year
Log(1+Active Years)	Number of years between an inventor's first granted patent application and his/her last granted patent application

Appendix B Constructing the inventor samples

B.1 Employer-Employee link for inventors

The PatentsView database makes it possible to track inventors' mobility across different organizations, such as firms, research institutes, and government agencies. Specifically, since a patent's assignee is most likely the employer of the inventor, an employer-employee link (i.e., inventor-assignee link) can be established in the year when the inventor files a patent that is ultimately granted to the organization.[1] However, the actual process is more complex due to the existence of patents with multiple assignees and the multiple patents an inventor may file in a given year. In such cases, additional steps are taken to disambiguate the inventor's employer based on various factors, such as geographic location and previous employment records (Liu et al., 2023, Li and Wang, 2023). The detailed process is described below.

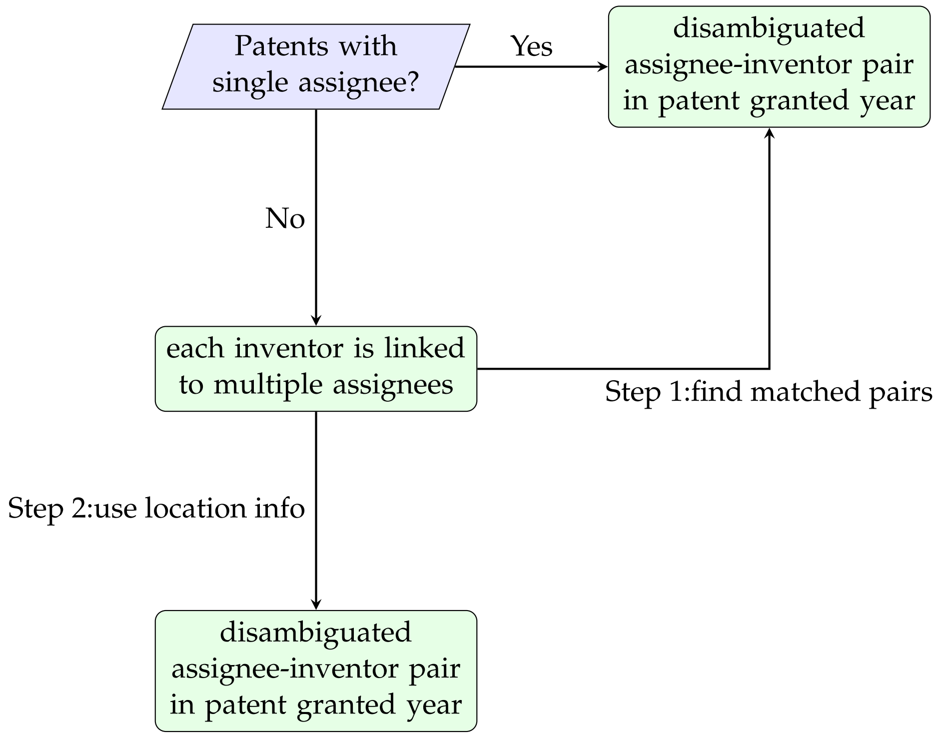
For patents assigned to a unique assignee, the inventor-assignee link can be unambiguously determined in the patent's granted year. For patents assigned to multiple assignees, I follow procedure discussed in Liu et al. (2023) and Li and Wang (2023) to disambiguate assignees for each inventor based on known information. First, I determine the assignee for each inventor using the matched information from patents with a unique assignee. Next, for the unmatched patents in this sample, I identify the assignee for each inventor based on their geographic locations. PatentsView provides precise and disambiguated longitude and latitude data for each inventor and assignee, allowing me to select the assignee whose location is closest to the inventor's. Figure B1 depicts this disambiguation process.

After getting the disambiguated inventor-assignee-year pairs for each patent, I determine inventors' employers in the year they file a patent based on patent filing information. Specifically, if all the patents filed by a given inventor in a particular year are assigned to a single assignee, it is reasonable to assume that this assignee is the inventor's employer for that year. Otherwise, the assignee that owns the most of the inventor's patents is viewed as her employer in that year.[2]

[1]The shortcoming of this method is that such a link can only be observed for active inventors in years when they file patent applications.

[2]If multiple assignees own the most of the inventor's patents, I refer to the assignee from the previous year's match. If no match from the previous year is available, I randomly select one assignee from the group that owns the most of the inventor's patents in that year.

Figure B1: Disambiguation process for inventor-assignee pairs



This process results in a table indicating the assignee each inventor is associated with in a given year. Lastly, I fill in any missing years for the inventor-assignee pairs with the closest matches. If the inventor is linked with the same assignee in two successive observations, the same inventor-assignee pair is filled for all missing years in between. Otherwise, it is assumed that the change of employers occurs in the middle year between two patent filing years with different assignees.

A real example illustrating the structure of this table is provided in Table B1. An inventor has filed patents in year 2011, 2016 and 2020. Based on the associated assignees, the inventor changed employers from Apple Inc. in 2011 to Dropbox, Inc. in 2016, and remained at Dropbox through 2020. To account for the gap between patent filings, I assume the change of employment occurred in 2013 (i.e., the midpoint between 2011 and 2016: 2011 + int((2016-2011)/2)). Accordingly, the table shows the inventor as being employed by Dropbox, Inc. from 2013 to 2020, when the inventor filed the last patent application. This table allows me to trace the mobility of each inventor across organizations throughout their active patenting career. Moreover, it provides insight into inventors' employment history across various types of organizations, including public firms, private firms, research institutions (such as labs or universities), and government agencies.

Table B1: An instance that illustrates the inventor mobility across firms

Inventor ID	Application Year	Assignee ID	Assignee Name
fl:ho_ln:chin-8	2011	f94215a0-b0d5-4aba-88de-614ff1829c0c	Apple Inc.
	2016	419ddede-31fd-4f50-968c-72a1dfabaf28	Dropbox, Inc.
	2020	419ddede-31fd-4f50-968c-72a1dfabaf28	Dropbox, Inc.

B.2 Dynamic link between assignee IDs with CRSP firm identifiers

The NBER dataset has been widely used in research analyzing corporate innovation, primarily because it provides a dynamic link between disambiguated patent assignees and Compustat firms (Hall et al., 2001). However, its coverage of patent data only extends until 2006, making it less suitable for this study. To create a similar link between public firms and PatentsView assignee IDs that extends into recent years, I build on the bridge table from Kogan et al. (2017), which links patents by their unique patent IDs to CRSP firms, covering the period from 1926 to 2022.

The basic requirement for a valid link is that each assignee ID should only be associated with a unique CRSP firm, if available, in a given year. Figure B2 (a) illustrates the process of establishing a valid link between assignee IDs and CRSP identifiers for patents with a single assignee. In this group, the assignee ID in PatentsView can be unambiguously matched to public firms in CRSP during the patent's grant year. For example, a patent (ID=6489985) was assigned to the JDS Uniphase Corporation (assignee ID is 5567d1c8-edf0-463c-ac67-650a94d029ad) in 2002, and this patent has been matched to CRSP firm JDS Uniphase Corporation (permno=79879, permco=12583) using Kogan et al. (2017)'s bridge file. Therefore, a link between assignee ID = 5567d1c8-edf0-463c-ac67-650a94d029ad permno=79879 and permco=12583 is established for 2002. I document the assignee-permno/permco-year link from this group.

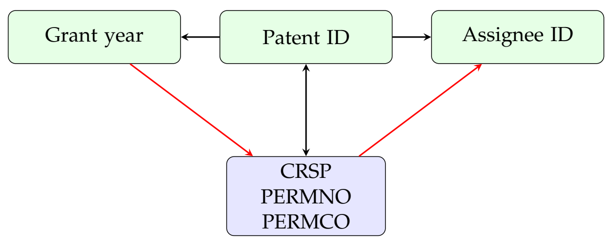
For patents with multiple assignees that can be matched with the bridge table by Kogan et al. (2017), I explore whether any additional information can be used to match assignee IDs with CRSP firms. For assignees not identified in the initial link, I exclude those that are matched with CRSP firms already documented by the above link. The rationale is that these assignees, which do not exclusively own a patent, are likely involved in strategic alliances or joint ventures with the innovating firms, which are already covered by the established link in the group of patents with a unique assignee.[3]

Next, I focus on assignees matched with CRSP firm identifiers that are not captured by the documented link and manually check the validity of the new assignee-CRSP link. I retain those where the assignee in PatentsView matches a CRSP company or is a subsidiary of a CRSP company. Additionally, I require the link between the assignee ID and CRSP permno/permco to be valid in the patent's grant year, based on the starting and ending dates of firm names provided by CRSP. The procedure is summarized in Figure B2 (b).

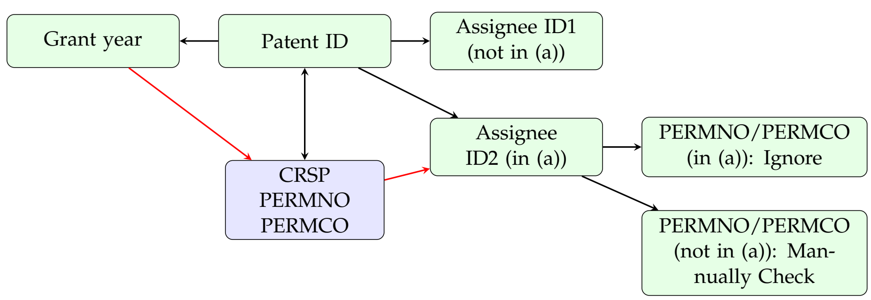
After combining these two samples of links, I address year gaps where no patents were granted to an assignee by filling in each missing year with the assignee's most recent match in CRSP firm identifiers. This results in a complete dynamic assignee-CRSP link throughout the entire sample period from 1976 to 2022.

[3] Here is an example that illustrates this process. A patent (ID = 7861805) was assigned to both Baker Hughes Inc. (assignee ID = 4e142d27-d6ea-46b2-b8a4-f8c5015aac6a) and US Synthetic Corporation (assignee ID = 300e4716-ef6c-484f-9dab-a3611f6470bd) in 2011. The first assignee is matched with the CRSP firm Baker Hughes Inc. (permno=75034, permco=20253) in the group of patents with a unique assignee, whereas the second assignee, being a private company, cannot be matched. In this case, I exclude the second assignee ID, and this patent provides no additional information for matching assignee IDs with CRSP firms.

Figure B2: Dynamic link of assignee IDs with CRSP identifiers



(a) Patents with unique assignee



(b) Patents with multiple assignees

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