Talent-Consolidating Mergers*

Alex Xi He†, Jing (Sophia) Xue‡

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Abstract

This paper argues that mergers that substantially increase firms' labor market power can weaken inventors' incentives to innovate by limiting the rents they capture from their innovations. We test this mechanism using individual-level longitudinal data from the U.S. Census Bureau. At both target and acquiring firms, inventors exposed to large increases in labor market concentration in already concentrated markets are rewarded less for patenting and produce fewer patents; they also earn lower wages and become less likely to change jobs after the merger. Our results are robust to comparing inventors within the same firm across technology fields and to controlling for field-specific shocks, and we find no comparable effects around failed mergers. Inventors at non-merging firms likewise experience declines in patenting and earnings when mergers increase concentration in their labor markets. Taken together, our findings show that labor market power shapes inventor incentives and productivity and constitutes an overlooked channel through which M&As affect innovation.

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†University of Maryland. Email: axhe@umd.edu

‡Georgia State University. Email: jxue@gsu.edu

1 Introduction

When firms merge, they consolidate not only products and assets but also workers, potentially reducing competition in the labor market (Naidu et al., 2018). This consolidation matters most for skilled workers, whose labor supply is inelastic and whose employment is concentrated in a small number of firms and industries (Nimczik, 2020; Seegmiller, 2025). Mergers that increase labor market concentration are known to lower wages (Prager and Schmitt, 2021; Arnold et al., 2026), but their effects may run deeper: if skilled workers anticipate capturing less of the value they create, their incentives to be productive weaken. Whether labor market power affects not just what workers are paid but what they produce remains an open question.

In this paper, we study how the labor market power created by mergers affects worker productivity, focusing on a group of high-skilled workers whose individual output is readily measurable: inventors. Inventors are the human capital driving firm-level innovation and growth, and firms seeking to innovate must compete for scarce inventive talent. We identify *talent-consolidating* mergers—mergers that raise labor market concentration and reduce competition for inventive talent—and show that they weaken inventors' outside options, suppress their incentives to innovate, and lower their innovation productivity. These findings shed light on how labor market power shapes the productivity of skilled workers, and highlight an important but often overlooked channel through which mergers affect innovation and growth.

To study how mergers affect inventor productivity, we use individual-level, longitudinal data from the U.S. Census Bureau. The data offer two unique advantages. First, building on the linkages developed in Akcigit and Goldschlag (2025), we can connect patent inventors to administrative employer-employee records containing comprehensive worker and firm information. Second, the administrative data let us examine a broad set of M&As, including acquisitions of smaller private firms that fall below antitrust review thresholds and are missed by standard databases such as SDC Platinum. Our final sample consists of around 3,300 mergers between U.S. innovative firms over the period of 2005–2017. We define an inventor as an employee of the target or acquirer firm who has at least one patent filed in the five years preceding the merger. There are 21,500 unique inventors in the target firms and 109,000 unique inventors in the acquirer firms. An average inventor has 0.7 patents per year.

To estimate the effect of increased labor market power induced by mergers, we compare the innovation and labor market trajectories of *high-labor-market-exposure* (hereafter, *high-exposure*) inventors, for whom the merger has a high predicted impact on labor market power, to those of *low-labor-market-exposure* (hereafter, *low-exposure*) inventors around M&As. We measure labor market power using labor market concentration following prior literature (e.g., Arnold, 2025), with two key modifications to account for the unique features of the inventor labor market. First, we use inventors' field of specialization instead of industry or occupation to define labor markets, given that inventors often move across industries and occupations but rarely move to a firm without existing inventors innovating in the same technological field. Second, rather than restricting labor markets within an local area, we use a data-driven approach to define geographical labor markets based on inventors' mobility patterns. We define high-exposure inventors as inventors who have an above-median labor market concentration before the merger and experience an above-median predicted increase in labor market concentration due to the merger. The impact on labor market concentration varies by an inventor's field and location, such that the same merger deal may significantly increase labor market power for some inventors while having little effect on others within the same firm.

We first document that high-exposure inventors capture a smaller share of surplus from their successful innovations following mergers. Following Toivanen and Väänänen (2012) and Kline et al. (2019), we estimate earnings changes of inventors in response to granted patents, where the value of patents are proxied by citation counts or excess stock market returns from Kogan et al. (2017). On average, inventors' earnings increase by 3–4% on average following a successful patent. However, for high-exposure inventors, the relationship between patenting and earnings is significantly weakened following mergers, and there is almost no increase in earnings following successful patents.

We then analyze the effects of M&As on inventor outcomes for high-exposure and low-exposure inventors by comparing each inventor at target or acquirer firms to a counterfactual inventor who has similar characteristics (e.g., patenting productivity, earnings, age, firm size, industry) but does not experience any merger event. We use a dynamic difference-in-differences specification to compare within-inventor changes in outcomes—each inventor relative to their matched counterfactual—between high- and low-exposure inventors over time. The key identifying assumption is that, in the absence of mergers, the gap between high-exposure inventors and their matched counterfactual

inventors would have evolved in parallel with the corresponding gap for low-exposure inventors.

Consistent with increased labor market power reducing incentives to innovate, we find that high-exposure inventors experience larger productivity declines relative to low-exposure inventors. High-exposure inventors at target firms have 0.13 fewer patents per year following the merger compared to low-exposure inventors, which is a 20% decline relative to the mean. High-exposure inventors at acquirer firms file 0.10 fewer patents per year (15% less than the average) compared to low-exposure inventors. Supporting our identifying assumption, the number of patents of high-exposure and low-exposure inventors as well as their counterfactual inventors exhibit similar trends before the merger, and the gap between high- and low-exposure inventors widens over time after the merger. The quality of patents by high-exposure inventors also declines, as evidenced by a larger drop in high-citation patents relative to low-citation ones after mergers.

We additionally examine how inventor outcomes vary with the merger's innovation synergy and degree of product market competition. A merger has high potential innovation synergy if the pre-merger innovations of the two merging firms exhibit high complementarity (measured by technology proximity from Jaffe (1986) and knowledge base overlap from Bena and Li (2014)) and low substitutability (measured by patent text similarity). We find that high-synergy mergers are associated with an increase in inventor productivity, whereas mergers in less competitive industries reduce inventor productivity. Nevertheless, controlling for synergy and product market competition leaves the gap between high- and low-exposure inventors unchanged.

The negative impact of labor market power on inventor productivity is quantitatively important. While high-exposure inventors make up only 20% of inventors in merger deals, a back-of-the-envelope calculation suggests they account for roughly a third of the overall decline in inventor productivity following mergers. At both target and acquirer firms, the productivity decline is concentrated among high-exposure inventors, while low-exposure inventors see a smaller decline or even a gain.

Next, we investigate how talent-consolidating mergers affect inventors' earnings and careers. High-exposure inventors earn less, both because they are less productive and because they capture a smaller share of the surplus from their innovations. Five years after the merger, high-exposure inventors experience 3.8% lower earnings at target firms and 3.2% lower earnings at acquirer firms relative to low-exposure inventors. They are also less likely to move to another firm or found their

own company after the mergers, consistent with a reduction in their outside options. In addition, decomposing the productivity effect by movers and stayers shows that high-exposure stayers account for most of the decline in patenting and earnings, supporting the interpretation that inventors who remain at the merged firm face weaker incentives to innovate.

We perform a series of tests to address threats to validity and alternative mechanisms. First, to control for deal-level unobserved shocks to innovation, we compare high- and low-exposure inventors within the same deal and the same firm, and find similar results. Second, to address shocks to the technological fields of high-exposure inventors, we show that matching to counterfactual inventors in the same field, or comparing high- and low-exposure inventors within the same, field yields similar results; We also find larger effects in fields with an upward innovation trend, indicating that the results are not driven by high-exposure inventors being in declining fields. Third, the results are robust to controlling for national concentration in the inventor's technology field, indicating that the effects operate through increased local labor market concentration rather than broader consolidation in innovation. Fourth, we find no comparable effects for high-exposure inventors around failed mergers, and opposite effects for the reverse treatment of spinoffs. Finally, higher labor market concentration is associated with lower labor R&D but not lower non-labor R&D, suggesting that the effects on high-exposure inventors do not stem from reduced firm investment.

Higher labor market concentration also creates negative spillovers on inventors at other firms in the same labor market. When a talent-consolidating merger substantially increases concentration in a market (a technological field by commuting zone), inventors at non-merging firms in that market also experience sharp declines in patenting and earnings. This analysis controls for field-by-year and commuting-zone-by-year fixed effects, absorbing field-specific and local shocks to inventor productivity. These spillover results provide another powerful test of the labor market power channel: the affected inventors are not party to the merger—and hence independent of the deal and its drivers—and the effects are confined to the labor market where the merger consolidates inventive talent: inventors in the same field but other locations, or the same location but other fields, are unaffected.

Finally, we investigate the impact of higher labor market power created by mergers on firm profits. Using a subsample of matched publicly listed firms, we find that, unlike innovation synergy, which is positively correlated with ex-ante takeover premiums and post-merger abnormal

ROA, changes in labor market concentration have little association with premiums or post-merger performance. This reflects the offsetting effects of labor market power: lower inventor productivity reduces firm profits, but firms also extract more rents from successful innovations and retain more inventors. Indeed, once we account for retention, the decline in patents that high-exposure inventors file with their original employer is much smaller than the decline in their total patenting, and is statistically insignificant. Overall, these results suggest that labor market power is unlikely to be a primary motivation for mergers.

Our paper makes two main contributions. First, we demonstrate that labor market power affects not only wages but also worker productivity. The setting of inventors, who are high-skilled workers whose individual output is measurable, allows us to show that reduced outside options weaken incentives to innovate, translating labor market power into real productivity losses rather than a pure transfer from workers to firms. Second, we identify labor market power as a distinct channel through which mergers affect innovation: beyond product market competition or technological synergies, the consolidation of inventive talent itself suppresses inventor productivity and lowers innovation output following mergers.

We contribute to several branches of literature. First, our paper relates most closely to the literature on mergers and labor market power. Arnold et al. (2026) and Prager and Schmitt (2021) show that mergers that increase local labor market concentration lead to lower worker earnings. More generally, prior work documents the negative wage effects of M&As (e.g., Lagaras, 2025; He and le Maire, 2025) and of higher labor market concentration (Azar et al., 2022; Benmelech et al., 2022; Schubert et al., 2025). Our setting of patent inventors, combined with worker-level administrative data, allows us to observe individual output, the share of surplus accruing to workers, and job mobility—providing new evidence on how higher labor market power induced by mergers shapes worker productivity and labor market dynamics.

Second, we contribute to the literature on mergers and innovation. Prior work documents innovation synergies (Bena and Li, 2014; Li and Wang, 2023), the outsourcing of R&D to target firms (Higgins and Rodriguez, 2006; Phillips and Zhdanov, 2013), organizational frictions (Seru, 2014), stress (Danis et al., 2026), "killer" acquisitions (Cunningham et al., 2021), and the role of mergers in resolving hold-up problems in innovation investment (Bena et al., 2023), among other channels. We propose a distinct channel—mergers weaken inventor incentives by reducing

labor market competition—which is the key insight of Fulghieri and Sevilir (2011) but has not been tested empirically. Moreover, we broaden the usual focus on publicly listed target firms by studying targets and acquirers jointly in a comprehensive set of deals covering both public and private firms. Finally, our paper focuses on the innovation productivity of individual patent inventors employed at the merging firms before the deal, tracking them over time, and thus complements studies of innovation output at the firm level.

Finally, we contribute to the literature on the determinants of inventor careers and productivity. With the availability of large administrative datasets characterizing the population of inventors, recent work sheds light on the origins of inventors (Bell et al., 2019), the individual returns to innovative activity (Toivanen and Väänänen, 2012; Kline et al., 2019), the role of team-specific human capital (Jaravel et al., 2018; Baghai et al., 2024), the effect of research funding and individual wealth on inventor productivity (Babina et al., 2023; Bernstein et al., 2021), and the reallocation of inventors across firms (Hombert and Matray, 2017; Brav et al., 2018; Xue, 2024). Bernstein (2015) and Akcigit and Goldschlag (2023) show that where inventors work matters: when inventors' employers go public, or when inventors move from young firms to incumbent firms, their earnings increase while their innovative output declines. Our evidence shows that changes in labor market competition due to M&As can also have large and persistent effects on inventors' productivity and careers.

2 Conceptual Framework

In Appendix A, we present a simple model to illustrate how mergers affect inventor incentives. At the start of each period, inventors can invest in human capital. The innovation project has two phases: in the first phase, inventors generate an idea with a probability that depends on ex-ante human capital investment; in the second phase, inventors and their firms develop the innovation together. We assume that human capital is unobservable to firms, and that firms and inventors cannot write binding contracts contingent on the development of successful ideas following Hart and Moore (1990). Inventors and firms bargain over the surplus from the innovation between the two phases, and they can withdraw their participation from the innovation project before the second phase and transfer their human capital to other firms. The outcome of bargaining depends on

their relative bargaining power and each party's outside option. In this model, mergers can affect innovation through labor market power, synergy, or product market power. Below, we discuss intuitions and predictions for these non-mutually-exclusive channels.

Labor Market Power. While inventors are rewarded for the value of the innovations they generate (Kline et al., 2019), the extent to which they can capture these rewards depends critically on their outside options. A merger reduces outside options in two ways. First, for workers in the merging firms, the merger absorbs rival employers into the same firm, removing them as outside options. Second, the merger raises labor market concentration and reduce competition in the labor market for inventors. A growing literature, including Arnold (2025) and Jarosch et al. (2024), shows that higher labor market concentration allows firms to impose larger "markdowns" on worker earnings relative to their marginal product. Caldwell and Danieli (2024) show that workers' outside options depend on the variety of firms they can move to. By reducing that variety, higher labor market concentration directly limits these options.

The labor market power channel predicts that mergers reduce the share of surplus and wages received by inventors. Inventors' human capital investment and innovation productivity also go down as a result of lower expected return from their investment. In addition, inventors have lower job mobility following mergers because their set of outside options shrinks. These effects are stronger when inventors' labor market are highly concentrated and when mergers have a large positive impact on labor market concentration for inventors.

Synergy. M&As may create innovation synergies between target and acquirer firms. These synergies can take several forms. First, firms may benefit from complementarities in knowledge, such as integrating distinct technological capabilities, research platforms, or intellectual property portfolios that become more valuable when jointly deployed (Bena and Li, 2014; Li and Wang, 2023). Second, mergers can facilitate more efficient allocation of innovative resources, for example, by streamlining overlapping R&D efforts, reallocating talent and capital toward the most promising projects, or scaling successful technologies more rapidly.

Innovation synergy lowers inventors' marginal cost of innovation, enabling them to produce more successful innovations for the same human capital investment. Inventors therefore invest more in human capital, innovate more, and earn higher wages. These positive effects are stronger

when the merging firms have complementary patent portfolios. The division of surplus between firms and inventors, however, remains unchanged.

Product Market Power. Mergers often reduce product market competition, which can have a negative effect on innovation incentives of the firm (Federico et al., 2017, 2020). Specifically, when two competitors merge, the combined firm internalizes the business-stealing externality that previously drove each firm to innovate aggressively. Before the merger, firms innovate partly to capture market share from rivals; afterward, innovation by one division cannibalizes the profits of another, reducing its net return. As a result, innovation becomes less valuable to the firm and the surplus from innovation decreases, and inventors reduce their human capital investment and innovation expecting to receive lower compensation.

Although the product market power channel also predicts declines in innovation and wages following mergers, it yields a set of implications that differ from those of the labor market power channel. First, the share of surplus captured by the inventor increases, in contrast to the decline predicted under labor market power. With the outside option held fixed, a reduction in total surplus implies that inventors capture a larger fraction of a smaller pie. Second, the product market power channel predicts that the decline in inventor productivity is largest when mergers occur between product market rivals in highly concentrated product markets, where the merger reduces product market competition the most, whereas the labor market power channel predicts the largest decline when the merger reduces labor market competition the most. Third, the product market power channel predicts increased separations of inventors, because the surplus from innovation is relatively higher at other firms, making outside options more attractive.[1]

3 Data

To study the impact of M&As on inventors, we use firm- and worker-level data from the U.S. Census Bureau. The firm-level dataset is the Longitudinal Business Database (LBD). The dataset covers all non-farm establishments with paid employees in the U.S. from 1987 to 2021. An establishment is defined as a specific physical location where business operations occur. The data provide in-

[1] More generally, we should see increased separations and a larger inventor share of surplus for any other mechanism that reduces the marginal value of innovation to the firm. For instance, if the target firm innovated primarily to make itself an attractive acquisition, the returns to further innovation fall once the deal is complete; the firm's demand for innovation weakens, and inventors should capture more of the remaining surplus and leave at higher rates.

formation on plant-level owner (firm), geographic location (state and county), industry (six-digit NAICS), employment, and payroll.

The worker-level dataset is the Longitudinal Employer Household Dynamics (LEHD). The LEHD data provide information on workers' employer, earnings, gender, race, and age. It is constructed using administrative records from the state unemployment insurance (UI) system and the associated ES-202 program. Worker earnings include salary and wage earnings as well as bonuses, exercised stock options, profit distributions, the cash value of meals and lodging, tips, and other gratuities in most states and, in some states, deferred compensation benefits like employer contributions to 401(k) plans and phantom stock plans. We have access to LEHD worker-level data from 22 states and the District of Columbia, which covers about half of the U.S. population and two thirds of all inventors.[2] The LEHD earnings data are currently available from the 1980s through 2021 (the start date varies across states and ranges from 1985 to 2002). While we include earnings from all employers, we associate workers with their "dominant" employer (i.e. the employer for which the worker earns the highest income) in each year.

For part of our analysis, we also use the Research and Development Surveys (RADS) from the Census Bureau, which cover a large sample of public and private US firms.[3] We match the R&D surveys to the LBD data to get a panel dataset on firms' R&D expenditures. The surveys ask respondents to report annual investments in total R&D, along with the type of expenditure (labor, materials, depreciation or other). While different firms may report R&D differently, our analyses will always exploit within-firm variation in R&D, therefore differencing out any systematic firm-specific reporting bias. Our main outcome variables are based on domestic R&D performed by a firm, which can be consistently observed across the surveys, and we performed various consistency checks to verify that all variables in our analysis are measured comparably across the change in survey instruments.

Inventor Data. To match inventors to workers in the LEHD, we use linkages between inven-

[2]The 22 states are: Arizona, Arkansas, California, Colorado, Delaware, Illinois, Indiana, Iowa, Kansas, Maryland, Missouri, Montana, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Pennsylvania, Tennessee, and Virginia.

[3]It combines information from four surveys: the Survey of Industrial Research and Development (SIRD) for the period 2000–2007, the Business R&D and Innovation Survey (BRDIS) for 2008–2016, the Business Research and Development Survey (BRDS) for 2017–2018, and Business Enterprise Research and Development (BERD) for 2019–2021.

tor records and the Census Bureau's disambiguated and anonymized person identifiers (known as Protected Identification Keys, or PIKs), developed by Akcigit and Goldschlag (2025).[4]

We use the U.S. Patent and Trademark Office (USPTO) data to identify the patents associated with each inventor. Our data cover all patents granted between 2000 and 2021. We use the application date to calculate the number of patents associated with each inventor in each year. In addition, we use the number of citations received by each patent to measure the quality of patents and patent technology classes to determine the technological fields of inventors. We also identify the commuting zone each inventor is located based on the patent filings and employer information. We describe these details in Appendix B.

Mergers and Acquisitions. We use the LBD to identify mergers and acquisitions. In the LBD data, when an establishment changes ownership, the establishment-level identifier remains unchanged, whereas the firm identifier changes. As a result, we are able to infer M&As by observing when firm-level identifiers change (Maksimovic and Phillips, 2001; Arnold, 2025; Tate and Yang, 2023). To avoid spurious changes in firm identifiers unrelated to mergers, we only keep cases where two or more firm identifiers of establishments merge into one. For example, if establishment 1 has firm identifier A and establishment 2 has firm identifier B in a year, and they both have firm identifier A in the following year, we infer that the two establishments merge where firm A is the acquirer and firm B is the target. We drop cases where the new firm identifier did not exist before the merger, in which case we cannot identify the acquirer or target. We keep only full mergers, where all establishments of the target are acquired by the same acquirer.

The main benefit of relying on the LBD for detecting M&A activity is its comprehensive coverage of small, privately held firms. Under the Hart-Scott-Rodino (HSR) Act, firms are not required to report acquisitions valued under $50 million (Wollmann, 2019), which leaves many acquisitions of smaller firms unreported and not captured in standard M&A databases like SDC Platinum.

The key outcome variables are patenting and annual earnings of inventors. For example, if two firms merged in July 2010, only patenting activity and earnings after July 2010 would be affected by the merger. In the data, we would observe that the merger happened between 2010 and 2011. Therefore, the effect at year zero should be interpreted as a partial effect of the merger, as some

[4]The match uses inventor name and location, as well as assignee-firm linkages. See Akcigit and Goldschlag (2025) for details.

earnings and patents in year zero may precede the merger.

4 Empirical Strategy

In this section, we describe our empirical strategy. First, we discuss how we measure labor market power using our inventor-firm matched data. Second, we describe our matching strategy to match each inventor in a target or acquirer firm to a "counterfactual" inventor with similar characteristics but working in a firm without any M&As. Finally, we specify a dynamic difference-in-differences model to identify how the impact of mergers on inventor outcomes depends on labor market power.

4.1 Measuring Labor Market Power

Because we will test how the impact of mergers depends on labor market power, we first need to measure it. Here, we follow the recent labor economics literature in proxying labor market power with labor market concentration. Prior work has documented that higher labor market concentration allows firms to impose larger "markdowns" on worker earnings relative to marginal product (Arnold, 2025; Benmelech et al., 2022; Schubert et al., 2025).

To measure labor market concentration, we need to define the labor market for inventors. For each inventor, the relevant labor market is the set of firms where the inventor would plausibly move to, which represents the inventor's outside options (Nimczik, 2020; Caldwell and Danieli, 2024; Jarosch et al., 2024). Table 1 presents statistics on inventor mobility across industries, commuting zones, and technological fields conditional on switching firms. It shows that most inventor moves are across industries: only 32% of inventors move within the same 2-digit NAICS industry, and 18% within the same 4-digit NAICS industry.[5] However, conditional on having at least one patent after moving, almost all inventors move to a firm innovating in the same technological field: for example, 95% of inventors move to another firm that has at least one inventor who has a patent in the inventor's main 4-digit technological field.[6] This is because inventors often work in teams with other inventors in the same field (Jaravel et al., 2018; Bhaskarabhatla et al., 2021; Baghai et al., 2024). This suggests that an inventor's relevant outside options are firms with inventors innovating

[5]Similarly, Bjelland et al. (2011) show that over half of employer-to-employer flows are across 11 super-sectors (which are coarser than 1-digit NAICS industries).

[6]For each inventor, we take the field with the most number of patents as the main technology field.

in the same field. We therefore define labor markets for inventors by technological field rather than by industry.

High-skilled workers like inventors tend to be more geographically mobile than the average worker (Moretti and Wilson, 2017; Amior, 2024). Table 1 shows that 16% of inventors move across commuting zones when they change jobs. We therefore define labor markets without imposing a local geographic restriction. Instead, following the occupation-mobility-adjusted approach of Schubert et al. (2025), we construct a geography-mobility-adjusted concentration measure that defines labor markets from observed inventor mobility.

Specifically, for an inventor in technology class m and commuting zone c, the mobility-adjusted Herfindahl-Hirschman Index (HHI) is defined as:

$$HHI_{mc}^{MA} = \sum_{i=1}^{N} s_{imc}^2 = \sum_{i=1}^{N} \left(\frac{\sum_p n_{imp} \times 1(\pi_{c \to p}^m > x)}{\sum_p n_{mp} \times 1(\pi_{c \to p}^m > x)} \right)^2, \tag{1}$$

where s_{imc} is firm i's market share for technology class m and commuting zone c, and n_{imp} is the number of inventors whose main technology class is m in firm i in commuting zone p. Technology class m is measured at the 4-digit CPC subclass level and there are around 600 technology classes in total.[7] The dummy $1(\pi_{c \to p}^m > x)$ equals one if the probability of moving from commuting zone c to p for inventors in technology class m (conditional on changing employers) is greater than some threshold x (e.g., 0 or 1%).[8] Intuitively, the labor market for inventors in technology class m and commuting zone p contains commuting zone c if the probability of moving from p to c for inventors in that field is sufficiently high. For example, if biotech inventors often move from Boston to the Bay Area, a merger between two Boston-area firms would have a smaller impact on the mobility-adjusted HHI because the biotech inventors in the Boston area still have a lot of outside options in the Bay Area. Note that this measure is asymmetric: commuting zone p may not be in the labor market for inventors in commuting zone c even when commuting zone c is in the labor market for inventors in commuting zone p. We consider variations of the baseline measure in Section 5.6.

We then calculate the predicted change in HHI due to the merger for inventors in technology

[7] With roughly 430 four-digit and 1,000 five-digit NAICS industries, the granularity of a four-digit CPC subclass falls between the four- and five-digit NAICS levels. As a robustness check, we also use 3-digit CPC codes.

[8] We describe how we measure the commuting zone of each inventor in Appendix B.3.

class m in commuting zone c as:

$$\Delta HHI_{mc}^{MA} = 2s_{amc}s_{tmc} = 2\left(\frac{\sum_p n_{amp} \times 1(\pi_{c\to p}^m > x)}{\sum_p n_{mp} \times 1(\pi_{c\to p}^m > x)}\right)\left(\frac{\sum_p n_{tmp} \times 1(\pi_{c\to p}^m > x)}{\sum_p n_{mp} \times 1(\pi_{c\to p}^m > x)}\right), \quad (2)$$

where n_{amp} and n_{tmp} are the number of inventors in technology class m in commuting zone p in the acquirer and target firm respectively.

We split our sample into high-exposure inventors, who are more affected by the merger in terms of labor market power, and low-exposure inventors. Following Arnold (2025), we define high-exposure inventors as those with an above-median initial level of HHI in the year before the merger and an above-median predicted change in HHI resulting from the merger.[9] Therefore, high-exposure inventors are inventors working in fields where inventors are concentrated in a small number of firms and both the target and acquirer firms are large players. However, Appendix Table A1 shows that there are many high-exposure inventors even in firms in the lowest size quintile or the lowest firm age quintile, because small and young firms can also be important players in a niche technological field. Since concentration is defined at the inventor level and depends on the inventor's field and location, each firm can have both high-exposure and low-exposure inventors simultaneously for the same merger event. In our merger sample, 22% of inventors are high-exposure inventors and 26% of merger events have at least one high-exposure inventor.

4.2 Matching to Counterfactual Inventors

We construct the inventor sample as follows. We refer to an inventor-year observation as experiencing a year-t merger event when (i) the worker has at least one patent filed within the past five years (and eventually granted); (ii) the worker has positive earnings in year $t-1$, with earnings of at least \$2,000 in all four quarters;[10] and (iii) the worker's dominant firm (the firm with the highest earnings) in year $t-1$ is either a target or an acquirer of a merger event between year $t-1$ and t.

We then match each such inventor-t observation to a "counterfactual" inventor-t observation that satisfies the following criteria: (i) the dominant firm in year $t-1$ did not experience any M&A activity within the (-5, +5) year window; (ii) the worker has at least one patent within the recent

[9] We calculate the medians for the sample of target inventors and the sample of acquirer inventors separately. We also separately examine the effect of the intial level of HHI and the predicted change in HHI in the empirical analysis.

[10] We require inventors to have positive earnings in all four quarters to exclude inventors who join or leave the firm during the year.

five years; (iii) the worker has earnings no less than $2000 in all four quarters of year $t-1$; and (iv) the observation matches the treated inventor-year observation along the following five dimensions:

- The inventors were in the same age cohort;
- The inventors were in the same quintile based on the number of patents between year $t-1$ and $t-5$;
- The inventors were in the same decile based on the average annual earnings between year $t-1$ and $t-5$;
- The dominant firms in year $t-1$ had the same two-digit NAICS industry code;
- The dominant firms in year $t-1$ were in the same size quintile (based on employment).

Matching on these various dimensions helps in identifying counterfactual inventors that would plausibly exhibit common trends to treated inventors in the absence of M&As. If multiple inventor-t observations satisfy all the criteria, we select the one with the most similar number of patents over the past five years as the counterfactual inventor. We also consider alternative matching criteria in later sections of the paper, including matching on inventors' technological fields.

We then construct a balanced panel of inventor outcomes for each treated inventor i and the matched counterfactual inventor i' from five years before to five years after the merger event.[11] For around 80% of target firm inventor observations and 75% of acquirer firm inventor observations, we are able to match them to a counterfactual inventor observation. Our final sample comprises 160,000 matched pair-year observations for target firms and 2,210,000 matched pair-year observations for acquirer firms from 3,300 merger events between 2005 and 2017.[12] Figure 1 plots the number of mergers in each year. Table 2 reports summary statistics from this sample. As the table shows, treated inventors and counterfactual inventors have similar patenting activities and earnings as a result of our matching procedure.

Appendix Figures A1 and A2 plots the distribution of inventors across industries and technological fields. We see that the inventors in our sample span across all industries, with the highest

[11] If an inventor experienced multiple events during our sample period, we construct a balanced panel with treated and counterfactual inventors for each event.

[12] We restrict to mergers in 2005–2017 since the LEHD data are available for most states from 2000 to 2021, and this allows us to observe the inventors from five years before to five years after the mergers.

concentration in manufacturing and tech sectors ("Information" and "Professional Services"). The technological fields with the largest numbers of inventors are "Computing; Calculating or Counting (G06)" (16% of target inventors and 22% of acquirer inventors) and "Electric Communication Technique (H04)" (18% of target inventors and 15% of acquirer inventors). Appendix Figure A3 further plots the distribution of high-exposure inventors by technological fields. Over half of the high-exposure inventors are concentrated in three 3-digit CPC classes that are common in the tech sector: "Computing; Calculating or Counting (G06)," "Information Storage (G11)," and "Electric Communication Technique (H04)." This suggests that mergers tend to have a large impact on labor market power in the tech sector due to the high concentration of inventors.

4.3 Empirical Specification

We estimate the impact of mergers on high- and low-exposure inventors using a difference-in-differences specification that exploits within-inventor variation: we track each inventor's outcomes relative to their own pre-merger levels, benchmarked against a matched counterfactual inventor. In particular, let i denote a treated inventor in a target or acquirer firm and i' denote the matched counterfactual inventor. Let j denote the firm-event combination.[13] For each matched pair-year observation in a given year s, we compute the difference in the outcome of interest between the treated inventor and the counterfactual inventor, denoted as $\Delta Y_{ii's} = Y_{is} - Y_{i's}$. We then regress the difference on event-time indicators:

$$\Delta Y_{ii'js} = \alpha Post_{ijs} + \gamma Post_{ijs} \times HighLaborMarketExposure_{ij} + X'_{ijs}\beta + \varepsilon_{ijs}, \tag{3}$$

where $Post_{ijs}$ equals one if inventor i experienced a merger event (denoted by j) before year s, and $HighLaborMarketExposure_{ij}$ is an indicator for high-exposure treated inventor. The control variables X_{ijs} include an indicator for pre-merger periods,[14] the high-exposure dummy $HighLaborMarketExposure_{ij}$, and the interactions between the pre-merger indicator and the high-exposure dummy. We cluster standard errors at the firm-event level j. In this specification, γ reflects the differential impact of mergers on high-exposure inventors relative to low-exposure

[13] For a given event, firm refers to the firm identifier of the inventor in year $t-1$.

[14] The indicator equals one if year s is two to five years before the merger event. We include this indicator such that the estimated effect compares post-merger periods to the year before the merger $t-1$, but we obtain similar results when we drop the indicator and compare post-merger periods to all pre-periods.

inventors.

We also consider a dynamic event study specification as follows:

$$\Delta Y_{ii'js} = \sum_{l \in -5,-4,-3,-2,0,1,2,3,4,5} (\gamma_l D^l_{ijs} \times HighLaborMarketExposure_{ij} + \mu_l D^l_{ijs} \times LowLaborMarketExposure_{ij}) + \epsilon_{ijs}, \tag{4}$$

where D^l_{ijs} is an indicator for inventor i having experienced the merger event (denoted by j) l years in the past, and $LowLaborMarketExposure_{ij}$ is the complement of $HighLaborMarketExposure_{ij}$. The coefficients of interest, γ_l (and μ_l), provide the time path of the difference in outcomes between high-exposure (and low-exposure) inventors and their counterfactual inventors relative to the year before the merger event, which is normalized to zero.

5 Main Results

5.1 Effects on Surplus Captured by Inventors

To test whether mergers reduce the outside options and rewards for high-exposure inventors, we first examine how the share of surplus from innovations captured by inventors changes around mergers. Previous literature documents that inventors get monetary rewards for their innovations: for example, Kline et al. (2019) show that the earnings of inventors rise by roughly $16,900 following patent allowance in the US, and Toivanen and Väänänen (2012) show that inventor earnings increase by 3% in the year of the patent grant in Finland.

We estimate how inventor earnings respond to patent allowance before and after mergers using the following specification:

$$w_{ijs} = \mu g_{ijs} + \beta Post_{ijs} \times g_{ijs} + \gamma Post_{ijs} \times HighLaborMarketExposure_{ij} \times g_{ijs} + X'_{ijs}\beta + \alpha_{ij} + \mu_t + \varepsilon_{ijs}, \tag{5}$$

where g_{is} is the value of patents granted to inventor i in firm j at year s, where the value of patents are proxied by citation counts or excess stock market returns from Kogan et al. (2017). The coefficient β measures the post-merger change in the share of patent surplus captured by inventors, and γ measures how this change differs for high-exposure inventors. We control for inventor-firm

fixed effects and year fixed effects, so that identification comes only from within-job-spell earnings changes. We also control for all two-way interactions between g_{ijs}, the post-merger dummy, and the high-exposure dummy.

Table 3 presents the results for log earnings. Panel A uses patent citations and Panel B uses the economic value of patents from Kogan et al. (2017). Column 1 shows that patenting is associated with a significant increase in inventors' earnings: for example, an average patent (with 10 citations) increases earnings by 3.6%, which is roughly in line with the estimates in previous studies by Toivanen and Väänänen (2012) and Kline et al. (2019). Column 2 shows that the earnings response to a patent with 10 citations becomes 4.7% lower for high-exposure inventors following mergers, thus high-exposure inventors get almost no increase in earnings following a successful patent. Columns 3 to 6 further examine earnings responses to citation-weighted patent counts in the preceding two or three years, accounting for the potential lag between patenting and earnings increase. We find similar results using the economic value of patents in Panel B. As columns 3 and 4 show, a granted patent worth \$10 million raises an inventor's earnings by 4% on average, with the reward falling by 1.5 percentage points for high-exposure inventors after the merger. Appendix Table A2 shows similar results using the level of earnings.

In all specifications, we find that the relationship between patenting and inventor earnings becomes much weaker following high-exposure M&As, suggesting that high-exposure inventors capture a smaller share of surplus from their successful innovations following mergers.

5.2 Effects on Inventor Productivity

We next examine the effect of mergers on innovation outputs by inventors. The main dependent variable is the number of patents applied for in a given year that are eventually granted. Table 4 presents the results. Column 1 shows that high-exposure inventors employed by the target firm have 0.139 (standard error = 0.066) fewer patents per year than low-exposure inventors employed by the target firm following mergers. Given that the average number of patents per year is 0.67 for target inventors, this represents a 21% decline in the number of patents. Column 3 shows that high-exposure inventors at acquirer firms experience a similar productivity decline: relative to low-exposure inventors, they produce 0.088 fewer patents per year following mergers, a 13% decline relative to the mean.

To control for the synergy and product market competition channels, we further interact the post-merger dummy with potential synergy whether the merger has high potential innovation synergy, whether the target firm is in a high-concentration industry, and whether the merger is horizontal. We measure potential innovation synergies based on the complementarity between the pre-merger patent portfolios of target and acquirer firms, using two measures: 1) *Technology Proximity*, following Jaffe (1986), the cosine similarity of the two firms' patent counts across technology classes; and 2) *Knowledge Base Overlap*, from Bena and Li (2014), the number of patents in the common knowledge base—those cited by both the acquirer's and the target's patents with award years from $t-5$ to $t-1$. Innovation synergies are also lower when the two firms' innovations are substitutable, which we capture via the text similarity of their pre-merger patent portfolios and consider separately in our analysis (see Appendix B.1 for details). We define high-synergy inventors as those with above-median complementarity on both technology proximity and knowledge overlap, and below-median substitutability on text similarity.

Columns 2 and 4 show that high-synergy inventors at target firms go on to patent more after the merger, consistent with Bena and Li (2014), who likewise find that technological overlap between merging firms is associated with greater post-merger innovation. Interestingly, higher text similarity between the two firms' patents is associated with a patenting decline for target inventors but an increase for acquirer inventors. Appendix Table A3 shows that both complementarity measures raise target inventors' patenting, but only when text similarity is low.[15] We also find more negative effects when mergers occur in a high-concentration industry, consistent with the product market power channel. Importantly, the impact of labor market concentration remains unchanged with the additional controls, suggesting that the labor market power channel operates independently of the other channels.

We next examine the dynamic effects of mergers on inventor productivity. Figure 2 plots the raw number of patents for high-exposure and low-exposure inventors and their respective control inventors. Before the merger, high-exposure and low-exposure inventors follow similar patenting trends, and both move in parallel with the matched control inventors, even though we did not match on trends. Because we condition on having a patent before the merger but not after,

[15] When text similarity is high, target and acquirer firms conduct very similar innovations, and acquirer firms may engage in "killer acquisitions" to discontinue target's innovation efforts and preempt future competition (Cunningham et al., 2021).

patenting declines naturally for all groups post-merger. Even so, high-exposure inventors at target and acquirer firms stand out with the largest decline.

Figure 3 plots the effects on the number of patents by high-exposure and low-exposure inventors estimated from equation 4. It confirms that the pre-trends are not statistically significant and that there is a significant drop in patenting for high-exposure inventors after the merger. The gap between high-exposure and low-exposure inventors widens over time, due to the lag between the time when an inventor invests in human capital and the time of filing a patent.

How does the quality of patents change following mergers? To measure patent quality, we consider the number of forward citations normalized by patent technology class and grant year. We define high-citation patents as those with above-median citations in a year, and low-citation patents as those with below-median citations. Table 5 shows that for high-exposure inventors at both target and acquirer firms, the decline in patenting is larger for high-citation than low-citation patents. These results indicate that mergers with a large impact on labor market power reduce valuable and influential innovation at both target and acquirer firms. The pattern also weighs against the interpretation that the decline in patenting reflects merged firms trimming defensive or duplicative patent filings: such filings are concentrated among low-value patents, whereas the decline we observe is steepest precisely for the most-cited ones.

5.3 Effects on Earnings and Job Separations

We next explore the effects of M&As on inventors' earnings and job separations. Earnings should decrease for high-exposure inventors due to lower innovation output and lower reward from innovation as shown in Section 5.1. Table 6 presents the results on inventors' log annual earnings. When all covariates are included in columns 2 and 4, high-exposure inventors at target firms have 3.8% (standard error = 1.8%) lower earnings than low-exposure inventors, and high-exposure inventors at acquirer firms have 3.2% (standard error = 1.3%) lower earnings. In Appendix Table A4, we use earnings normalized by pre-merger earnings instead of log earnings to accommodate zero values, and find similar results.

Panels (c) and (d) of Figure 3 plot the earnings of high-exposure and low-exposure inventors relative to control inventors over time. In both target and acquirer firms, high-exposure inventors suffer much post-merger larger earnings losses than low-exposure inventors. For example, five years

post-merger, high-exposure inventors earn 9.6% less in targets and 6.7% less in acquirers, versus 3.5% and 1.8% for low-exposure inventors. Notably, there is a jump in the earnings of target inventors in the first year following mergers, which is likely due to target inventors realizing gains from their equity holdings. This mirrors the earnings increase following PE buyouts documented in Isen et al. (2026) using IRS data, suggesting that our earnings measure partially captures workers' equity compensation, such as phantom stock payouts and stock options.[16] However, this temporary increase is more than offset by the subsequent decline in earnings among high-exposure inventors.

Table 7 looks at the effects on separation rates of inventors. We define the separation rate as whether the inventor is no longer employed by the dominant employer in year -1.[17] Therefore, the separation rate is cumulative and is set to one once the inventor leaves the firm and joins another firm. We find that high-exposure inventors are less likely to move to other firms after the merger: their separation rates decline by 6.9% and 3.8% more than those of low-exposure inventors in target and acquirer firms, respectively, reflecting a greater reduction in outside options for high-exposure inventors. Panels (e) and (f) of Figure 3 show that only high-exposure target inventors are more likely to stay, whereas low-exposure target inventors are more likely to move to other firms following the merger.[18]

Some inventors separate from incumbent firms to found their own startups. We examine departures to entrepreneurship in Appendix Table A5, where entrepreneurship is a dummy equal to one if the inventor separates from the original firm and is part of the founding team at a new firm. We find that high-exposure inventors are also less likely to leave to start their own firms at both target and acquirer firms following mergers.[19]

[16] While we cannot earnings into their components, we find that the increase in the first year is concentrated in target inventors whose firms are publicly listed prior to being acquired, which is consistent with target inventors cashing out their equity holdings.

[17] For target inventors, the separation rate is one after the merger if the inventor is employed at a firm other than the acquirer firm. Therefore, for workers moving between the target and acquirer firms post-merger, the separation rate is zero.

[18] This may be due to a poor fit (e.g., culture clash) between the target inventors and the acquirer firm (Kim, 2024). Previous studies also document higher departure rates of target firm employees following M&As, especially among key employees like executives (Martin and Mcconnell, 1991; Lagaras, 2025).

[19] This could stem from lower earnings and startup funding, worse employment options if the startup fails, or greater difficulty in hiring early talent as the merger raises labor market power.

5.4 Confounding Factors and Threats to Validity

Our empirical strategy compares high-exposure inventors, for whom the merger substantially affects labor market power, with low-exposure inventors. The identifying assumption is that, absent the merger, the gap between high-exposure inventors and their control inventors would have moved in parallel with the gap between low-exposure inventors and their control inventors. While it is reassuring that high-exposure and low-exposure inventors, as well as their control inveotors, display parallel pre-trends, in this section we conduct additional tests to further rule out confounding factors and threats to validity.

Within-Deal Comparison. One threat to validity is that mergers may coincide with other unobserved shocks to firm innovation. To control for firm-level time-varying confounding factors, we include event-firm-year fixed effects, comparing high- and low-exposure inventors across different fields or commuting zones within the same firm and the same merger deal.

Table A6 presents the results. Similar to the baseline results, we find significantly larger declines in patenting, earnings, and separation rates for high-exposure inventors in both target and acquirer firms. For example, with all the additional controls in column 2, high-exposure inventors file 0.121 fewer patents per year at target firms and 0.059 fewer patents per year at acquirer firms. In Table A7, we further include event-firm-CZ-year fixed effects and only compare inventors within the same firm, same merger deal, and same commuting zone. The estimates remain similar, though they become less precise for target firm inventors. Because target firms are smaller, they contain fewer inventors per firm-commuting zone cell, which reduces the within-cell variation available for identification and widens the confidence intervals. Overall, these results suggest that any unobserved firm-level or regional-level shocks are unlikely to explain our results.

Field-Specific Shocks. Another concern is that high-exposure inventors may be in technology fields with unobserved negative shocks to innovation outputs that coincide with the merger. For example, firms may wish to consolidate their R&D efforts through mergers in declining technological fields. While the absence of pre-trends for high-exposure inventors alleviates this concern, we conduct several additional tests to further address it.

First, we re-match target or acquirer inventors to counterfactual inventors in the same tech-

nological field (and keeping all other matching criteria unchanged). As a result, any field-specific trends are differenced out when we compute the difference between treated and counterfactual inventors. Appendix Tables A8 and A9 present the results when matching within the same 3-digit and 4-digit CPC subclass. The matching rate becomes lower with more stringent matching criteria, but estimates for high-exposure inventors remain similar.

Second, we split inventors into high- and low-exposure groups within 4-digit technological fields so that we only compare inventors within the same field but experiencing mergers with different changes in labor market concentration. Appendix Table A10 shows similar results.

Third, we separately estimate the effects in rising vs. declining technological fields measured by pre-merger growth in the number of patents in the field. Appendix Table A11 shows that the effects are, if anything, stronger in growing fields, indicating that they are not driven by declining productivity in the fields where high-exposure inventors work.

Finally, we construct a measure of the merger's impact on concentration in the innovation field as a whole. This measure differs from our labor market concentration measure in that it is based on national market shares, whereas labor market shares are commuting-zone specific, so the two can diverge: a merger can raise national concentration in a field while leaving local inventor labor markets relatively unaffected. If firms consolidating innovation also face negative shocks around the merger, inventors exposed to mergers with a large impact on innovation concentration should show larger patenting declines, independent of labor market power. In a horse race including both measures, Table A12 shows that the merger's impact on innovation concentration is not significantly associated with patenting declines, and that controlling for it leaves the effect of labor market concentration unchanged. These findings indicate that our results are unlikely to be driven by high-exposure inventors being concentrated in fields that are simultaneously declining in productivity and consolidating across firms, and that the effects we document are specific to rising labor market concentration rather than higher concentration in the innovation field per se.

Failed Mergers and Spinoffs. To further rule out confounding factors, we conduct a placebo exercise using failed mergers—deals that were announced but not completed. Firms involved in failed mergers share many characteristics with those in completed mergers, such as merger motivations and innovation dynamics, making them a useful quasi-control group for what would have happened

absent a completed merger (Seru, 2014). We identify failed mergers as those with a "Pending" status in the SDC Platinum Database, and match their target and acquirer firms to the Census datasets by firm name and address, as detailed in Appendix B.2. Table A13 reports the effects using the same specification as Table 4. We find no statistically significant difference between high- and low-exposure inventors for any outcome at target or acquirer firms; the effects are close to zero and, in some cases, opposite in sign to those from completed mergers. This further alleviates the concern that high- and low-exposure inventors might follow different trends in firms that choose to merge.

We also explore the reverse treatment of spinoffs, where one firm splits into two stand-alone firms. Spinoffs should raise patenting by high-exposure inventors, since they increase labor market competition for inventors (Fulghieri and Sevilir, 2011).[20] Appendix Table A14 shows that following spinoffs, high-exposure inventors experience increases in patenting relative to low-exposure inventors, both overall and among those who join the spun-off firm. However, the difference is not significant, given the smaller sample of inventors involved in spinoffs.[21]

5.5 Heterogeneous Effects

If high-exposure inventors have lower productivity after mergers because of higher concentration and worse outside options, the effects should be larger for more mobile inventors who are more responsive to external opportunities. Appendix Table A15 explores this by interacting pre-merger inventor characteristics with treatment. We find larger negative effects for the most productive, highly-paid, and highly-cited inventors at both target and acquirer firms. We also find smaller effects for older and higher-tenure inventors at acquirers, who likely have more firm-specific human capital and lower mobility.

Appendix Table A16 explores heterogeneity by ex-ante firm characteristics. For target-firm inventors, effects are generally stronger when the target is older and larger (or the acquirer younger

[20] We identify spinoffs in the LBD data: if the establishments of firm A split into firms A and B, where B is a new identifier, we call A the parent firm and B the spun-off firm. We match each inventor in the parent firm to a counterfactual inventor one year before the spinoff using the criteria in Section 4.2. High-exposure inventors are those with an above-median initial labor market HHI and a below-median predicted change in HHI (or an above-median absolute predicted change). We exclude cases where all inventors go into one firm and the predicted change in HHI is zero.

[21] There are fewer spinoffs than mergers, and in most cases all or nearly all inventors join one of the two firms, so the impact on labor market concentration is small.

and smaller)—cases where the two firms are more comparable and likely competed more fiercely for labor before the merger. Comparing public and private firms, effects are larger when the target is public and smaller when the acquirer is public, though neither difference is statistically significant. Appendix Table A17 further shows that the baseline results hold in the public-acquirer subsample, the sample typically studied in prior work.

5.6 Robustness and Additional Results

In this section, we show that our results are robust to alternative definitions of high-exposure inventors and labor market concentration, as well as to alternative matching strategies.

Alternative Definitions of High-Exposure Inventors. While our baseline definition of high-exposure inventors uses both the initial level and the change in HHI, Appendix Table A18 separately explores the effects of the level versus the change in concentration. The table shows that both the level and the change matter: inventors with a high initial level or a high predicted change in HHI alone experience some negative effects, but the largest decline in patenting occurs for inventors with both a high initial level and a high predicted change.

Appendix Table A19 sorts inventors into quartiles based on the predicted change in labor market HHI. The effects on patenting are monotonic in the predicted change, with the largest negative effects in the top quartile. Effects on earnings and separation rates are likewise largest for inventors with the greatest predicted increase in HHI.

Alternative Measures of Labor Market Concentration. We consider five alternative measures of labor market concentration. First, we use the coarser 3-digit CPC code to measure technology classes in Panel A of Appendix Table A20. Second, we use a higher cutoff of 1% to define geographical markets so that commuting zone p is in the same labor market as commuting zone c for an inventor only if the probability of inventors in that inventor's technology class moving from c to p exceeds 1%. The results are shown in Panel B of Table A20. Third, in Panel C, we count the number of inventors with *any* patent in technology class m when calculating n_{imp} and n_{mp} in equation 1. Fourth, we use a weighted average of HHI and change in HHI across all technology classes to define high-exposure inventors in Panel D. Specifically, for inventors with patents in multiple technology classes, we define $HHI_i^{MA} = \sum_m s_{im} HHI_{mc}^{MA}$ and $\Delta HHI_i^{MA} = \sum_m s_{im} \Delta HHI_{mc}^{MA}$,

where s_{im} is the share of inventor i's patents in technology class m during the five years before the merger. Fifth, in Appendix Table A21, we weight each inventor by the number of patents filed in the previous five years, then compute each firm's labor market share as its weighted share of inventors in the market. Across all measures, we find that high-exposure inventors have lower patents, earnings, and separation rates following mergers, with similar magnitudes to the baseline estimates.

Alternative Matching. Our baseline matching between treated and control inventors does not condition on field, and fewer than 10% of matched pairs fall in the same 4-digit field. We showed in Section 5.4 that matching on technological field produces similar results. In Appendix Table A22, we instead match each treated inventor to a control inventor in the same 4-digit field but a different commuting zone, to minimize spillovers; this too yields similar results.[22]

Since we match inventors in the year before the merger, one concern is that inventors may anticipate the merger before that and change their behaviors or leave the firm (and thus missing from our sample). To address this, we re-match treated inventors to counterfactual inventors *three* years before the merger using the same criteria, and redefine high- and low-exposure inventors based on information available before year $t-3$. Since most of the mergers occur within one year of announcement,[23] this analysis should not be contaminated by news about the merger. However, measurement errors could be higher because some of the "treated" inventors left the firm before the merger occurred and are not directly affected by the treatment. Appendix Table A23 shows that all of our results remain similar when matching inventors three years before the merger, suggesting that any bias due to anticipation is quantitatively small.

5.7 Decomposition Between Job-Movers and Job-Stayers

So far, we have compared the outcomes of inventors initially employed by target or acquirer firms with those of counterfactual inventors, regardless of whether they remain at the merged firm. To understand whether job-movers or job-stayers drive the effects, we decompose the effects of mergers

[22] Even without requiring matches to come from different commuting zones, most matched pairs are already in different CZs, and thus likely in different labor markets. Consistent with negative spillovers on inventors in the same field and same commuting zone, the estimates in Table A22 are slightly larger than the estimates in Table A9. We later estimate the spillover effects directly in Section 6.1.

[23] In the SDC data, 98.0% of mergers are completed within one year of the announcement date, and 99.7% of mergers are completed within three years of the announcement date.

on high-exposure inventors between the two. We write the mean outcome for treated inventors as $y_t = y_t^m \delta_t + y_t^s(1-\delta_t)$, where y_t^m and y_t^s are the average outcomes among treated movers and stayers, and δ_t is the treated separation rate. The counterfactual mean is defined analogously, $y_c = y_c^m \delta_c + y_c^s(1-\delta_c)$. These identities let us decompose the treated–control difference $y_t - y_c$ as

$$y_t - y_c = \underbrace{(y_t^m - y_c^m)\delta_c}_{\text{Movers}} + \underbrace{(y_t^s - y_c^s)(1-\delta_c)}_{\text{Stayers}} + \underbrace{(y_t^s - y_t^m)(\delta_c - \delta_t)}_{\text{Separation rate}} \tag{6}$$

Equation 6 apportions the observed difference into three parts: the mover and stayer outcome gaps, each scaled by the (counterfactual) separation rate or its complement, and a separation-rate term scaled by the outcome gap between treated stayers and movers. We compute each component for high- and low-exposure inventors and use it as the dependent variable in equation 4.[24]

Figure 4 summarizes the results from the decomposition. For each period, we plot the effects on high- and low-exposure inventors (relative to counterfactuals) as two bars, each split into the three components of equation 6. Panel A shows that for target inventors, the stayer gap accounts for almost all of the high-exposure decline in patenting. Panel B shows that for acquirer inventors, both stayers and movers contribute, with stayers explaining the larger share; the lower separation rate of high-exposure acquirer inventors partly offsets this, since stayers patent more than movers. Panels C and D show similar patterns for earnings. Overall, the decline in patenting and earnings among high-exposure inventors is driven primarily by high-exposure stayers underperforming low-exposure stayers, consistent with weaker incentives and investment for inventors who remain at the merging firms.

5.8 Quantitative Magnitudes

To assess the quantitative magnitudes of the labor market power channel, we estimate the average effect of mergers on inventor outcomes in Appendix Table A24. On average, inventors reduce their patenting by 0.097 patents per year at target firms and 0.036 at acquirer firms. Given that low-exposure inventors patent 0.062 fewer per year at targets and 0.024 fewer at acquirers in Table 4,

[24] Each year, δ_t and δ_c are the fractions of treated and counterfactual inventors no longer employed by the original firm. We construct each component of equation 6 by aggregating the treated–counterfactual outcome differences, scaled by the respective separation rates, and use the result as the dependent variable in equation 4. For the mover component, for example, we scale the treated-mover outcome by δ_c/δ_t before differencing against the counterfactual-mover outcome.

this suggests that the labor market power channel explains about a third of the overall decline in patenting following mergers.

Appendix Figure A4 plots the effects of mergers on the number of patents for eight groups of inventors split by exposure to the merger's impact on labor market power, innovation synergy, and industry concentration. It shows that at both target and acquirer firms, mergers have large and significant negative effects on patenting only when they have a large impact on labor market power. When the impact on labor market power is low, the effects on patenting are close to zero, and sometimes positive when there is high synergy. This highlights that labor market power is an important driver of the negative effects of mergers on inventor productivity.

6 Mechanisms and Discussion

In this section, we provide additional tests of the labor market power mechanism and discuss other alternative mechanisms. We then explore how the labor market power channel affects firm profits and post-merger performance.

6.1 Market-Level Effects

For mergers that substantially increase labor market power, we should expect them to also reduce the outside options of inventors at other, non-merging firms in the same labor market. These inventors should therefore experience lower earnings and face weaker incentives to innovate. To test this, we estimate the effect of talent-consolidating mergers on market-level innovation output and inventor earnings.

We construct the market-level sample following a procedure similar to the one used for the inventor-level sample. Each market is defined as a 4-digit technological field by commuting zone cell. For each year t, we compute the predicted change in labor market concentration in every market k due to merger activity, denoted by ΔC_k^{MA}. We define an event as a change in HHI due to mergers by 100 points (or 1 percent). All markets have at most one event during the sample period. We estimate the following specification around these events:

$$y_{kt} = \lambda_k + \delta_t + \sum_{l \neq -1} \eta_l D_{kt}^l + \gamma_{mt} + \mu_{ct} + \epsilon_{kt}, \tag{7}$$

where D_{kt}^{l} is an indicator for market k being l periods away from the event at calendar time t. We include 4-digit field-by-year fixed effects γ_{mt} and commuting-zone-by-year fixed effects μ_{ct} to absorb field-specific and commuting-zone-specific trends. The dependent variable y_{kt} is the total number of patents or log average inventor earnings of market k in year t *excluding* firms that had M&As during the sample period so that we focus on spillovers and net out any direct impacts on the merging firms. To estimate the event-study coefficients, we adopt the interaction-weighted estimator of Sun and Abraham (2021).[25] Standard errors are clustered at the market level.

We first test whether talent-consolidating mergers in fact generate persistent increases in labor market concentration for inventors. Any increase may instead be transitory if mergers induce more entry. Panel (a) of Figure 5 shows that mergers do indeed produce a persistent increase in labor market concentration, raising it by 1 to 2 percent over the five years following the merger.

Panels (b) and (c) of Figure 5 show that both patenting and inventor earnings at non-merging firms decline following talent-consolidating mergers. The absence of pre-trends supports a causal interpretation, and the effects grow steadily over time. These results confirm that mergers which raise labor market power generate negative spillovers onto non-merging firms in the same labor market. Appendix Table A25 presents the static effects, where we impose a constant coefficient for all post-treatment periods.[26] On average, mergers increase inventors' labor market HHI by 100 points or more reduce the number of patents in the market by 126 and inventor earnings by 1.3%. The earnings effects at non-merging firms are smaller than those at merging firms for two reasons. First, beyond the rise in labor market concentration, inventors at merging firms face an additional loss of outside options, as the merger converts what were previously competing employers into part of the same firm, removing them as outside options. Second, because labor markets are defined with measurement error, some firms innovating in the same field may not in fact compete directly for labor with the merging firms, attenuating the measured spillover.

[25] Unlike the conventional two-way fixed-effects estimator, this approach remains consistent when treatment effects are heterogeneous across cohorts, avoiding the contamination from negative weighting that can otherwise distort dynamic estimates (de Chaisemartin and D'Haultfœuille, 2020).

[26] This corresponds to the static specification in Sun and Abraham (2021): $y_{kt} = \lambda_k + \delta_t + \sum_{l=-5}^{-2} \mu_l D_{kt}^{l} + \mu_g \sum_{l>0} D_{kt}^{l} + \gamma_{mt} + \mu_{ct} + \epsilon_{kt}$. The static effect is the average change in post-treatment periods relative to year -1 averaged across cohorts.

6.2 Firm Investment

Mergers may reduce firms' incentives to invest in R&D (Ornaghi, 2009; Szücs, 2014; Federico et al., 2017; Cabral, 2018; Haucap et al., 2019). Because our labor market channel operates through inventors' incentives to innovate, we examine whether our results might instead reflect firm-level reduction in innovation incentives and R&D investment.

First, although a reduction in firms' innovation incentives would also lead to lower innovation output, it carries different predictions than the labor market channel. It would predict that inventors capture a larger share of the surplus from successful innovations after the merger, and that separation rates rise, as inventors find their outside options relatively more attractive. We observe the opposite on both margins for high-exposure inventors: both the surplus share and the separation rate fall, contrary to what a decline in firm innovation incentives would predict.

Next, we test this directly using firm R&D data from the U.S. Census Bureau. In column 1 of Table 8, the dependent variable is R&D expenditure per worker at the firm level. We combine target and acquirer firms in the years before the merger, and retain only mergers for which we observe R&D consistently over time for both parties. High-exposure inventors are associated with lower post-merger R&D, though the difference is not statistically significant. Mergers in high-concentration industries and horizontal mergers, by contrast, reduce R&D significantly, which is consistent with the weaker incentive to innovate when two product-market rivals combine in an already concentrated industry. Because roughly two-thirds of R&D expenditure is labor compensation,[27] we decompose R&D into its labor and non-labor components in columns 2 and 3.[28] Labor R&D falls for high-exposure inventors, consistent with inventors being paid less as labor market power rises. However, non-labor R&D shows no corresponding decline. Higher industry concentration and horizontal mergers, by contrast, reduce both labor and non-labor R&D. Finally, column 4 uses the overall number of inventors in the technological field as an alternative measure of firms' innovation effort. Contrary to what lower firm innovation incentives would predict, firms do not reduce the number of inventors in the fields of high-exposure inventors.

Overall, our evidence suggests that although mergers can reduce firms' innovation incentives

[27] See the 2020 Business Enterprise Research and Development Survey (BERD) by NSF.

[28] Labor R&D is consistently observed only for a subsample of firms, so the samples in columns 2 and 3 are smaller than in column 1.

and R&D investment—particularly for horizontal mergers in less competitive industries—weaker firm innovation incentives do not drive the effects of labor market power that we observe for high-exposure inventors.

6.3 Impact on Firm Performance

How does the labor market power channel affect firm profits? Theoretically, the effect is ambiguous: on the one hand, greater labor market power enables firms to extract more surplus from innovation and retain more inventors; on the other hand, lower inventor productivity could harm firm profits.

We first show that higher inventor retention partly offsets the productivity losses. In Appendix Table A26, we re-estimate the baseline regression but replace the inventor's total patent count with the number of patents the inventor files conditional on remaining at the firm. The decline in patenting that high-exposure inventors assign to their original employer is far smaller than the decline in their total patenting, and it is statistically insignificant. Specifically, the effects are 40% smaller for target inventors (column 2) and 55% smaller for acquirer inventors (column 4) than the corresponding estimates in Table 4. This suggests that higher retention helps offset the loss in firm innovation output that would otherwise follow from lower inventor productivity.[29]

We then examine the effects on firm profits using the subsample of publicly listed firms. We match publicly listed target and acquirer firms to SDC Platinum to obtain merger premiums, defined as the ratio of the offer price to the target's pre-announcement stock price, and acquirers' post-announcement returns. In Table 9, each observation is a merger event, and we regress merger outcomes on the share of high-exposure inventors, synergy, and other deal characteristics. Column 1 shows that acquirers pay slightly higher premiums for mergers that increase labor market power, though the effect is not statistically significant. High-synergy mergers, by contrast, carry premiums 17 percentage points higher, indicating that bidders value synergies highly. Columns 2 to 4 examine cumulative abnormal returns (CARs) over 1-, 2-, and 5-day windows around the announcement date. Higher labor market power is associated with lower announcement returns. Innovation synergy is, perhaps surprisingly, also associated with lower announcement returns, suggesting that the market views the premiums paid for synergy as too high.

[29] This also partly explains why our inventor-level patenting estimates are more negative than those in some studies of firm-level patenting.

In the last two columns of Table 9, we turn to realized performance, measured by post-merger abnormal return on assets (ROA). Following Ben-David et al. (2026), we compute abnormal ROA as the acquirer's post-acquisition, industry-adjusted return on assets benchmarked against its pre-deal performance, over three- and five-year horizons. Synergy positively predicts post-merger ROA, whereas the effect of labor market power is small and statistically insignificant.

Overall, labor market power shows little association with merger premiums or post-merger performance. This reflects two offsetting forces: higher labor market power lowers inventor productivity but also raises inventor retention and lets the firm extract more rents from innovation. The tradeoff between these forces is heterogeneous across deals, and firms weigh it against the many other costs and benefits of a merger. Still, the results suggest that labor market power is unlikely to be the primary motivation or source of synergy for most merger deals.

7 Conclusion

This paper examines how the labor market power created by mergers affects inventor productivity. We show that talent-consolidating mergers—mergers that significantly raise concentration in inventors' labor markets—weaken inventors' incentives to innovate, lowering patenting, earnings, and job mobility at both target and acquirer firms.

Our results are relevant for policy. Antitrust authorities often challenge mergers over potential harms to innovation (Federico et al., 2020), but these arguments typically center on firms' incentives to innovate. A notable exception is the FTC's 2022 challenge to the proposed merger between Meta and Within, which cited reduced "pressure to compete for the most talented app developers" among the reasons to block the deal, noting that the talent needed to create triple-A VR experiences is scarce and highly concentrated. Our paper provides the first systematic evidence on the prevalence and effects of such talent-consolidating mergers, and the results suggest that this labor market consideration deserves attention beyond isolated cases: these deals can have quantitatively important negative effects on inventors' innovation productivity, operating through worker incentives rather than firm incentives alone.

More broadly, the detrimental effects of labor market power on the incentives and productivity of high-skilled workers may extend to settings beyond mergers and innovation. Many firms use

non-compete and anti-poaching agreements to restrict the mobility of their most talented workers, and some incumbents have recently acquired top talent from startups without formal mergers, bypassing antitrust scrutiny.[30] The mechanism documented in this paper may also apply to other high-skilled workers whose output depends on capturing the returns to their human capital, such as scientists, engineers, and executives. Understanding how labor market power shapes incentives and productivity in these settings represents a fruitful area for future research.

[30]See examples from Microsoft and Amazon.

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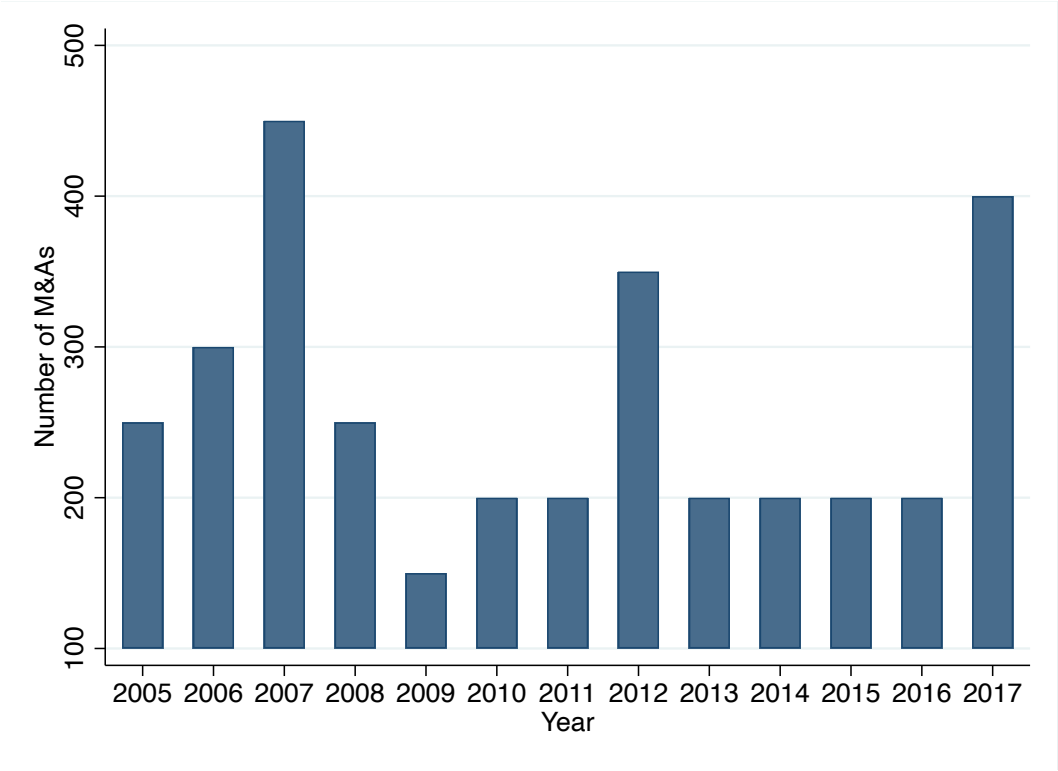
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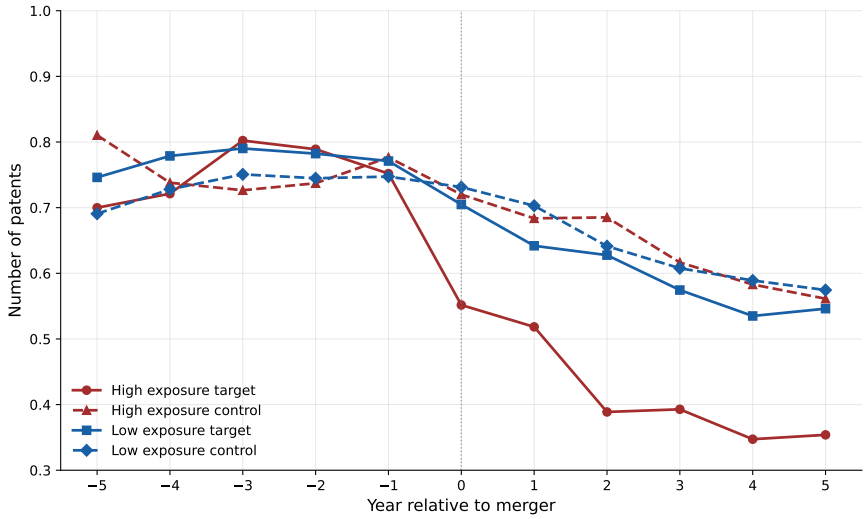
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Figure 1: Number of M&As by Year

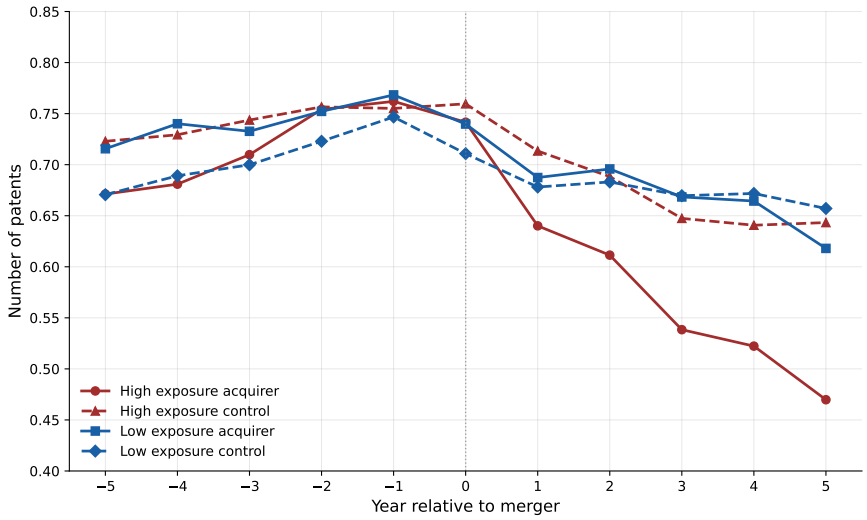


This figure plots the number of M&As in the U.S. each year between 2005 and 2017 in which the target firm has at least one active inventor. We define an inventor as an employee with at least one patent in the five years preceding the merger. The number of observations is rounded in accordance with the disclosure rules set by the U.S. Census Bureau.

Figure 2: Raw Trends of Patenting of Treated and Counterfactual Inventors



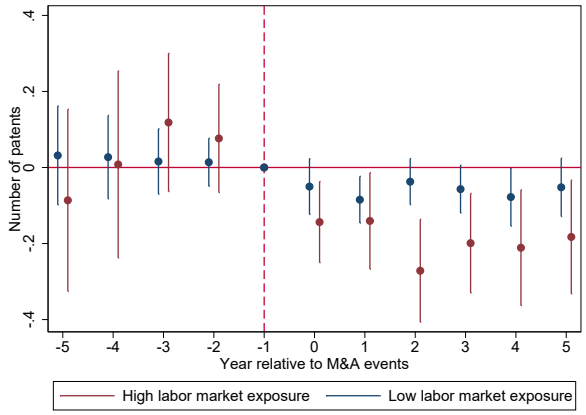
(a) Target Inventors



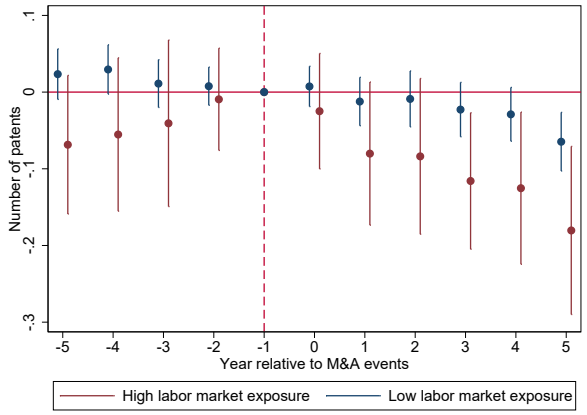
(b) Acquirer Inventors

This figure plots the raw trends in the number of patents of treated and counterfactual inventors from 5 years before the merger to 5 years after the merger. In each panel, we plot the average number of patents in each year for four groups of inventors: high-exposure treated inventors (in target firms in Panel (a) and acquirer firms in Panel (b)), low-exposure treated inventors (in target firms in Panel (a) and acquirer firms in Panel (b)), high-exposure counterfactual inventors, and low-exposure counterfactual inventors. High-exposure inventors are those for whom the merger has an above-median predicted impact on labor market concentration and the labor market has above-median initial concentration before the merger.

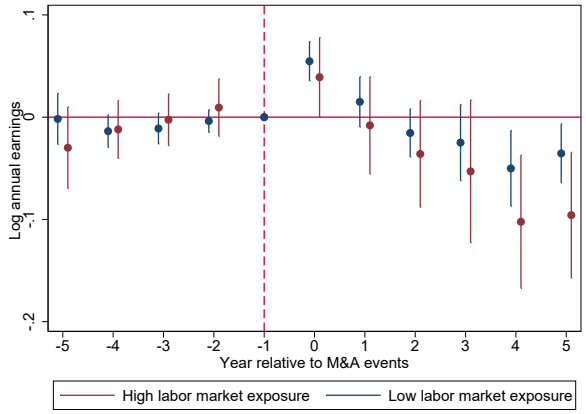
Figure 3: Changes in Inventor Outcomes around M&As for High-Labor-Market-Exposure and Low-Labor-Market-Exposure Inventors



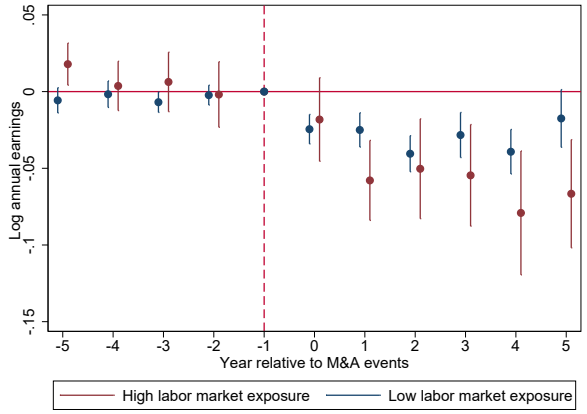
(a) Number of Patents, Target Inventors



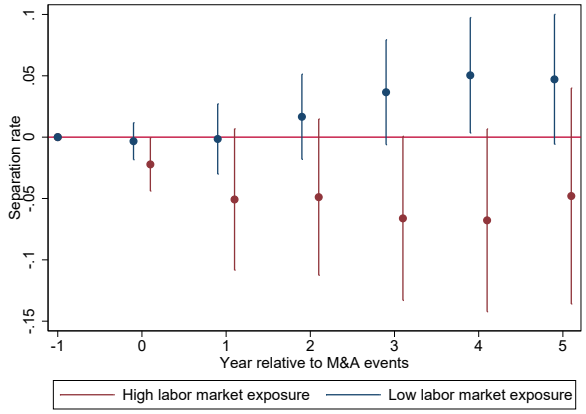
(b) Number of Patents, Acquirer Inventors



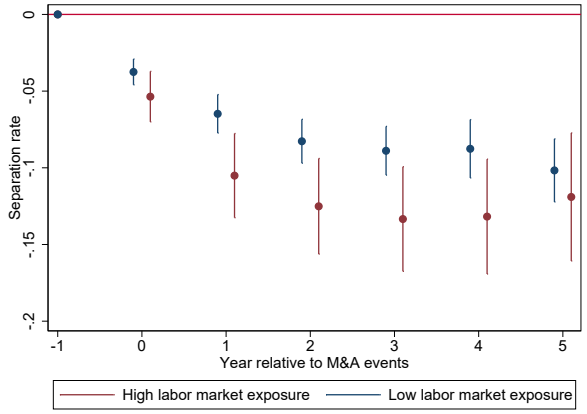
(c) Log Annual Earnings, Target Inventors



(d) Log Annual Earnings, Acquirer Inventors



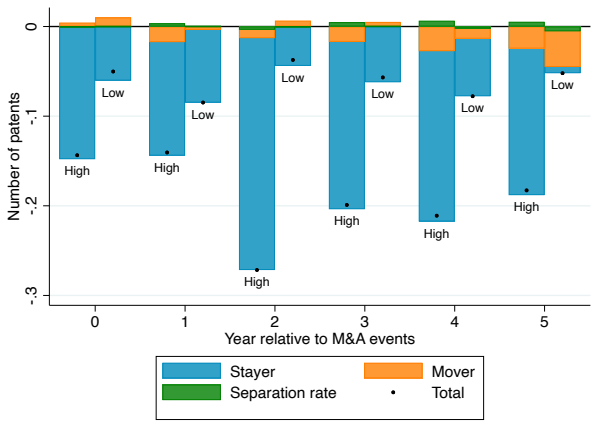
(e) Separation Rate, Target Inventors



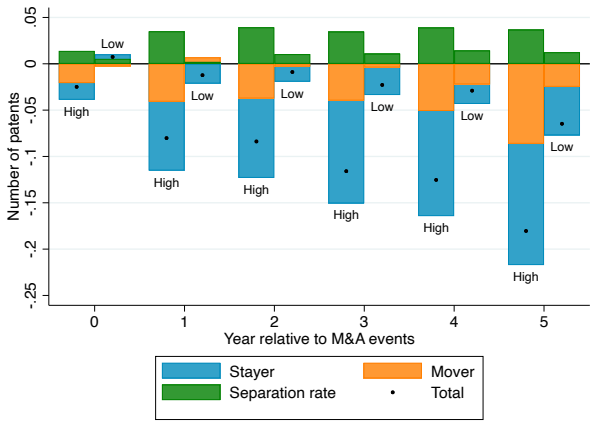
(f) Separation Rate, Acquirer Inventors

This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on inventor outcomes by high-labor-market-exposure and low-labor-market-exposure inventors based on equation 4. Panels (a), (c), and (e) show the estimates for target inventors, and Panels (b), (d), and (f) show the estimates for acquirer inventors. The dependent variables are the number of patents in Panels (a) and (b), log annual earnings in Panels (c) and (d), and separation rate in Panels (e) and (f).

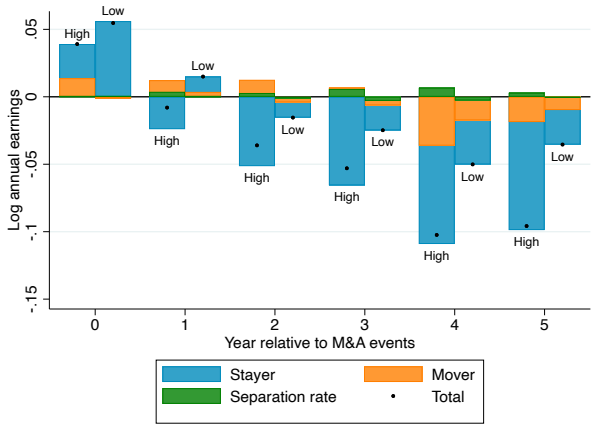
Figure 4: Decomposition of the Changes in Inventor Outcomes around M&As Between Stayers and Movers



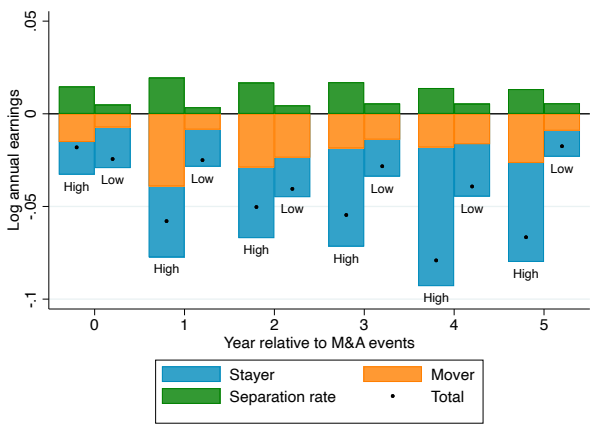
(a) Number of Patents, Target Inventors



(b) Number of Patents, Acquirer Inventors



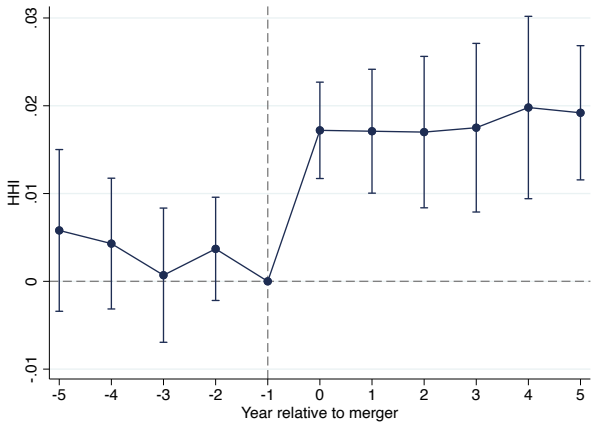
(c) Log Annual Earnings, Target Inventors



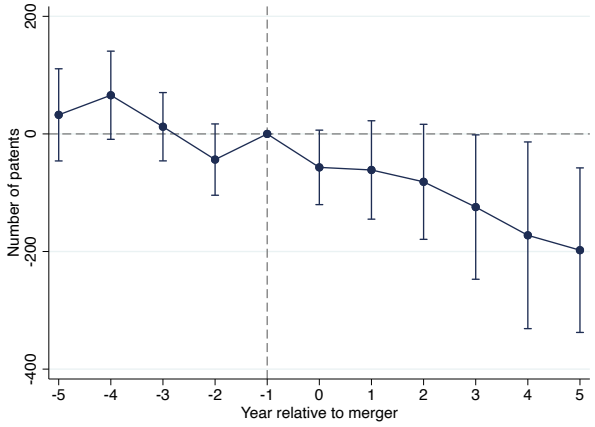
(d) Log Annual Earnings, Acquirer Inventors

This figure plots the decomposition of changes in inventor outcomes around M&As based on equation 6. For each post-merger period, two bars are shown representing the changes for high-labor-market-exposure and low-labor-market-exposure inventors (relative to counterfactual inventors) indicating. Each bar is further decomposed into three components: changes of stayers, changes of movers, and changes due to differences in separation rates. The black dots represent the sum of these three components. Panels (a) and (c) show the estimates for target inventors, and Panels (b) and (d) show the estimates for acquirer inventors. The dependent variables are the number of patents in Panels (a) and (b) and log annual earnings in Panels (c) and (d).

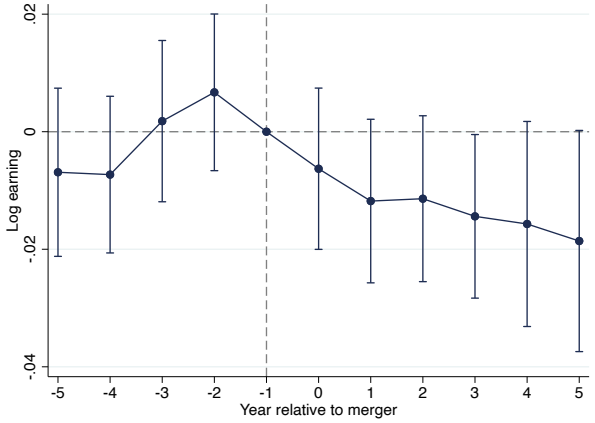
Figure 5: Changes in Market-Level Patenting and Wages around Talent-Consolidating Mergers



(a) HHI



(b) Number of Patents, Non-Merging Firms



(c) Log Annual Earnings, Non-Merging Firms

This figure plots the event-study estimates and 95% confidence intervals, where events are mergers with predicted change in labor market HHI over 100 points. The unit of observation is a labor-market-year. Each labor market corresponds to a commuting-zone-by-4-digit-technological-field cell. The dependent variables are labor market HHI in Panel (a), the number of patents filed by inventors at non-merging firms in Panel (b), and the log average annual earning of inventors at non-merging firms in Panel (c), where non-merging firms are firms not involved in a merger as acquirer or target throughout our sample period. All specifications include 4-digit tech field×CZ fixed effects, 4-digit tech field×Year fixed effects, and CZ×Year fixed effects. Standard errors are clustered at the labor market level. Stars denote standard statistical significance (***$p <$ 0.01, **$p < 0.05$, *$p < 0.1$, respectively).

Table 1: Summary Statistics of Inventor Mobility Patterns Across Firms

	Mean
Number of Inventor-Year Observations	7,290,000
Probability of Switching Firm	0.1510
Conditional on Switching Firm	
Probability of Moving Within 2-digit NAICS Industry	0.3177
Probability of Moving Within 3-digit NAICS Industry	0.2425
Probability of Moving Within 4-digit NAICS Industry	0.1822
Probability of Moving Within Commuting Zone	0.8442
Conditional on Switching Firm and Continuing to Patent	
Probability of New Firm Innovating in the Same 1-digit CPC Field	0.9683
Probability of New Firm Innovating in the Same 3-digit CPC Field	0.9566
Probability of New Firm Innovating in the Same 4-digit CPC Field	0.9455

This table reports summary statistics on inventor mobility patterns across firms. The top panel reports statistics for all inventor-year observations. The second panel conditions on inventor switching employers between consecutive years. The third panel further restricts the sample to inventors who have at least one patent after switching employers. All statistics and observation counts in this table are rounded in accordance with the U.S. Census Bureau's disclosure rules.

Table 2: Summary Statistics of Treated and Control Inventors

Panel A: Target Inventors

		Treated Inventors		Control Inventors	
	N	Mean	Std Dev	Mean	Std Dev
Age	160,000	45.52	9.002	45.61	9.080
Log Annual Earnings	160,000	12.00	0.7051	12.00	0.7034
Annual Earnings	160,000	251,400	1,909,000	243,000	1,311,000
Separation Rate	96,000	0.1889	0.3914	0.1870	0.3899
Number of Patents	160,000	0.6722	1.835	0.6436	1.492
Number of High-Citation Patents	160,000	0.3298	1.084	0.3392	0.9920
Number of Low-Citation Patents	160,000	0.3423	1.097	0.3044	0.8408

Panel B: Acquirer Inventors

		Treated Inventors		Control Inventors	
	N	Mean	Std Dev	Mean	Std Dev
Age	2,210,000	45.30	9.005	45.30	8.918
Log Annual Earnings	2,210,000	11.93	0.6276	11.95	0.6552
Annual Earnings	2,210,000	209,200	840,800	228,000	1,214,000
Separation Rate	1,353,000	0.1169	0.3213	0.1788	0.3832
Number of Patents	2,210,000	0.6828	2.041	0.6290	1.538
Number of High-Citation Patents	2,210,000	0.3310	1.187	0.3388	1.027
Number of Low-Citation Patents	2,210,000	0.3518	1.163	0.2902	0.8335

This table reports summary statistics for inventors at the target and acquirer firms and their matched counterfactual inventors. Panel A reports characteristics of target inventors and their matched counterfactual inventors. Panel B reports characteristics of acquirer inventors and their matched counterfactual inventors. The matching criteria are described in Section 4. All statistics and observation counts in this and subsequent tables are rounded in accordance with the U.S. Census Bureau's disclosure rules.

Table 3: Changes in Returns to Patenting around M&As

Panel A: Weighted by Citation

	Log Annual Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted Patents 1 Year	0.0036***	0.0023***				
	(0.0002)	(0.0003)				
Weighted Patents 1 Year × Post × High Exposure		-0.0047***				
		(0.0012)				
Weighted Patents 2 Years			0.0032***	0.0027***		
			(0.0002)	(0.0003)		
Weighted Patents 2 Years × Post × High Exposure				-0.0031***		
				(0.0008)		
Weighted Patents 3 Years					0.0030***	0.0027***
					(0.0001)	(0.0002)
Weighted Patents 3 Years × Post × High Exposure						-0.0021***
						(0.0006)
Obs	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000

Panel B: Weighted by Economic Value

	Log Annual Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted Patents 1 Year	0.0042***	0.0026***				
	(0.0002)	(0.0003)				
Weighted Patents 1 Year × Post × High Exposure		-0.0007				
		(0.0011)				
Weighted Patents 2 Years			0.0040***	0.0030***		
			(0.0002)	(0.0002)		
Weighted Patents 2 Years × Post × High Exposure				-0.0015**		
				(0.0007)		
Weighted Patents 3 Years					0.0039***	0.0032***
					(0.0001)	(0.0002)
Weighted Patents 3 Years × Post × High Exposure						-0.0016***
						(0.0005)
Obs	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000

This table reports the regression estimates from model 5. The dependent variable is log annual earnings. *Weighted Patents 1 Year* (*2 Years*, or *3 Years*) refers to the count of patents weighted by normalized citations (in Panel A) or economic value (in Panel B) that are granted within the preceding one (two, or three) years. The citations are normalized by patent technology class and grant year. The economic value of patents is measured using excess stock market returns following Kogan et al. (2017). The *Post* dummy indicates the years after the M&A event. The *High Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The sample contains all observations of treated inventors in target or acquirer firms. All regressions control for two-way interactions between weighted patent counts, the *Post* dummy, and the *High Labor Market Exposure* dummy. All regressions also include inventor-firm fixed effects and year fixed effects. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 4: Changes in the Number of Patents around M&As

	Target Inventors		Acquirer Inventors	
	Number of Patents			
	(1)	(2)	(3)	(4)
Post	-0.0623**	-0.0195	-0.0244	0.0135
	(0.0290)	(0.0355)	(0.0151)	(0.0343)
Post × High Labor Market Exposure	-0.1386**	-0.1321**	-0.0880**	-0.1024***
	(0.0661)	(0.0632)	(0.0381)	(0.0363)
Post × High Synergy		0.1919***		0.0354
		(0.0739)		(0.0509)
Post × High Text Similarity		-0.0831		0.0414
		(0.0507)		(0.0327)
Post × High Industry Concentration		-0.0788		-0.1054***
		(0.0673)		(0.0313)
Post × Horizontal		0.0199		-0.0266
		(0.0478)		(0.0350)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of patents based on equation 3. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in a given year. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p <$ 0.01, **$p < 0.05$, *$p < 0.1$, respectively).

Table 5: Changes in Patent Quality Measured by Citations around M&As

	Target Inventors		Acquirer Inventors	
	Number of High-Citation Patents	Number of Low-Citation Patents	Number of High-Citation Patents	Number of Low-Citation Patents
	(1)	(2)	(3)	(4)
Post	-0.0113	-0.0082	0.0119	0.0016
	(0.0255)	(0.0212)	(0.0218)	(0.0203)
Post × High Labor Market Exposure	-0.0711*	-0.0610*	-0.0740***	-0.0284
	(0.0380)	(0.0355)	(0.0237)	(0.0193)
Post × High Synergy	0.1114**	0.0805*	0.0106	0.0248
	(0.0546)	(0.0421)	(0.0298)	(0.0308)
Post × High Text Similarity	0.0135	-0.0966***	0.0353*	0.0061
	(0.0354)	(0.0299)	(0.0198)	(0.0200)
Post × High Industry Concentration	-0.0936**	0.0148	-0.0571***	-0.0483**
	(0.0433)	(0.0363)	(0.0178)	(0.0196)
Post × Horizontal	0.0365	-0.0166	-0.0057	-0.0208
	(0.0306)	(0.0292)	(0.0214)	(0.0236)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of high-citation and low-citation patents based on equation 3. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. In columns 1 and 3, the dependent variable is the difference between the number of patents with above-median citations (normalized by patent class and grant year) filed by the treated inventor and the number of patents with above-median citations filed by the matched counterfactual inventor. In columns 2 and 4, the dependent variable is the difference between the number of patents with below-median citations filed by the treated inventor and the number of patents with below-median citations filed by the matched counterfactual inventor. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 6: Changes in Inventors' Earnings around M&As

	Target Inventors		Acquirer Inventors	
	Log Annual Earnings			
	(1)	(2)	(3)	(4)
Post	-0.0187	-0.0052	-0.0305***	-0.0168
	(0.0129)	(0.0193)	(0.0060)	(0.0155)
Post × High Labor Market Exposure	-0.0346*	-0.0377**	-0.0303**	-0.0323**
	(0.0196)	(0.0177)	(0.0134)	(0.0126)
Post × High Synergy		-0.0651*		-0.0471**
		(0.0338)		(0.0184)
Post × High Text Similarity		0.0059		-0.0105
		(0.0279)		(0.0141)
Post × High Industry Concentration		-0.0179		0.0039
		(0.0243)		(0.0126)
Post × Horizontal		-0.0216		-0.0266*
		(0.0235)		(0.0160)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' earnings based on equation 3. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 7: Changes in Inventors' Separation Rates around M&As

	Target Inventors		Acquirer Inventors	
	Separation Rate			
	(1)	(2)	(3)	(4)
Post	0.0265	0.0618***	-0.0834***	-0.1014***
	(0.0181)	(0.0237)	(0.0073)	(0.0150)
Post × High Labor Market Exposure	-0.0827***	-0.0689***	-0.0390***	-0.0383***
	(0.0258)	(0.0234)	(0.0139)	(0.0137)
Post × High Synergy		-0.0111		0.0642***
		(0.0496)		(0.0241)
Post × High Text Similarity		-0.0807**		0.0327**
		(0.0331)		(0.0154)
Post × High Industry Concentration		0.0464		-0.0122
		(0.0349)		(0.0147)
Post × Horizontal		-0.0177		0.0065
		(0.0312)		(0.0182)
Obs	96,000	96,000	1,350,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' separation rates based on equation 3. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference in separation dummy between the treated inventor and the matched counterfactual inventor, where the separation dummy equals one if the inventor is no longer employed by the dominant employer in year -1. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 8: Changes in Firm R&D and Inventor Team Size around M&As

	Total R&D per Worker	Labor R&D per Worker	Non-Labor R&D per Worker	Log Number of Inventors in the Same Tech Field
	(1)	(2)	(3)	(4)
Post	5.939*	9.365***	6.084	0.1162***
	(3.422)	(3.373)	(3.862)	(0.0441)
Post × High Labor Market Exposure	-3.531	-5.701*	4.826	-0.0056
	(3.079)	(3.426)	(3.472)	(0.0361)
Post × High Synergy	-2.864	-5.466	1.483	-0.0067
	(4.256)	(4.439)	(5.669)	(0.0573)
Post × High Text Similarity	2.264	-1.676	4.411	-0.0347
	(3.426)	(3.258)	(4.471)	(0.0376)
Post × High Industry Concentration	-14.70***	-9.810***	-7.877*	-0.0291
	(3.126)	(3.741)	(4.597)	(0.0360)
Post × Horizontal	-5.729*	-3.043	-3.234	-0.0241
	(3.297)	(4.642)	(6.359)	(0.0414)
Obs	1,717,000	581,000	581,000	1,717,000

This table reports difference-in-differences estimates of the effect of M&As on inventor team size and R&D intensity at the firm level. The dependent variables are R&D expenditure per worker (in thousands of dollars) in column 1, labor component of R&D expenditure per worker (in thousands of dollars) in column 2, non-labor component of R&D expenditure per worker (in thousands of dollars) in column 3, and the difference between the treated inventor and the matched counterfactual inventor in terms of log number of inventors in the same 4-digit technological field within the same firm in column 4. All regressions include both target and acquirer inventors, and firm-level variables are calculated for the combined firm (combining target and acquirer firms) in years before the merger. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. We also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 9: Merger Premiums, Announcement Returns, and Post-Merger Performance

	Merger Premium	Acquirer CAR [-1, 1]	Acquirer CAR [-2, 2]	Acquirer CAR [-5, 5]	Abnormal ROA Year 1 to 3	Abnormal ROA Year 4 to 5
	(1)	(2)	(3)	(4)	(5)	(6)
Average Labor Market Exposure	0.0313	-0.0185*	-0.0238*	-0.0306*	0.0057	0.0223
	(0.0654)	(0.0099)	(0.0138)	(0.0162)	(0.0180)	(0.0239)
High Synergy	0.1666***	-0.0352***	-0.0287*	-0.0595***	0.0413***	0.0407***
	(0.0628)	(0.0121)	(0.0159)	(0.0197)	(0.0154)	(0.0152)
High Text Similarity	0.0294	-0.0081*	-0.0073	-0.0062	0.0167***	0.0245***
	(0.0357)	(0.0043)	(0.0049)	(0.0062)	(0.0062)	(0.0084)
Horizontal	0.0468	0.0071	0.0056	0.0109	0.0003	-0.0008
	(0.0352)	(0.0050)	(0.0058)	(0.0076)	(0.0052)	(0.0068)
Obs	250	800	800	800	800	800

This table reports OLS estimates of regressing outcomes of mergers (merger premiums, announcement returns, and post-merger abnormal ROAs) on merger characteristics. Each observation is a merger event. In column 1, the dependent variable is merger premium, defined as the ratio of the offer price to the target's stock price 1 day before the merger announcement. In columns 2 to 4, the dependent variables are log changes in the acquirer's stock price from t (t=1, 2, 5) days before the merger announcement to t (t=1, 2, 5) days after merger announcement. In column 5, the dependent variable is the merging firm's average abnormal ROA between one and three years after the merger. In column 6, the dependent variable is the merging firm's average abnormal ROA in year 4 and 5 following the merger. *Average Labor Market Exposure* is the average *High Labor Market Exposure* dummy for all inventors involved in the merger, where the *High Labor Market Exposure* dummy indicates that the merger has a high predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We also control for the HHI in the acquirer and target's industry at the time of merger (the estimates are suppressed due to Census disclosure rules). Standard errors are clustered at the event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Internet Appendix

A. Model

We outline a simple theoretical framework on merger and inventor incentives. We aim to introduce the simplest model necessary to capture the essence of a broad class of models featuring labor market power, synergy, and product market power and derive the empirical predictions that we can test using our data.

Suppose that there is a continuum of workers $\mathcal{I}$ and a continuum of jobs $\mathcal{J}$. We treat $\mathcal{I}$ and $\mathcal{J}$ as exogenous and of equal measure, which we normalize to 1. Each firm is a positive measure of jobs, and we define $\kappa : \mathcal{J} \to \mathcal{K}$ as the function that assigns jobs to firms. At the beginning of each period, each inventor $i \in \mathcal{I}$ matches with a job $j \in \mathcal{J}$ in firm k. After matching to a job, the inventor can invest in human capital $s_i \in [0, 1]$, which determines the probability of having a successful idea.[31] A successful idea can later be developed into innovation by the firm in the second stage. We assume that the cost of investing in human capital is convex and equals $\frac{1}{2}\gamma s_i^2$, where γ is the unit cost of investing in human capital.

We assume that inventors' human capital is not observable by firms. Following Hart and Moore (1990), we assume that the firms and the inventors cannot write binding contracts contingent on the development of successful ideas and that they can withdraw their participation from the project before the development phase. If an inventor generates an idea, the allocation of the surplus from the development of the innovation is determined at the interim date through bargaining between the firm and the inventor, before the the project is developed by the firm.

The outcome of bargaining between the inventor and the firm depends on their relative bargaining power and on each party's outside option. We assume that each firm's outside option while bargaining with its inventor is limited, since the firm cannot replace its current inventor with a new one from the general labor market population, but it can hire an inventor from only a rival firm in the same labor market. This assumption is justified if inventors need ex-ante human capital investment to develop innovation later, and relaxing this assumption and allowing the firm to hire a new inventor from the labor market does not change our results as long as the value created by

[31] s_i can also be interpreted as the effort exerted by inventors.

the firm and the new inventor is lower than the value created with the original inventor, due to the relationship-specific nature of the original inventor's human capital investment.

Suppose a successful idea from inventor i can be developed by firm k to create value y_{ik}. When inventor i bargains with firm k over the surplus upon having a successful idea, she gets:

$$w_{ij} = (1-\beta)E[w_{ij}|\kappa(j) \neq k] + \beta y_{ik}, \tag{8}$$

where $\beta \in (0,1)$ represents the inventor's bargaining power, and $E[w_{ij}|\kappa(j) \neq k]$ represents the outside option of the inventor. We assume that the inventor's human capital is at least partially transferrable to other firms in the labor market, and the outside option is the expected wage offer the inventor with a successful idea receives at jobs *outside* the current firm.

Caldwell and Danieli (2024) show that a wage equation similar to equation 8 can be derived from a two-sided matching model with idiosyncratic preferences using a notion based on cooperative game theory, where in equilibrium, no single inventor-firm combination could deviate from their current match and split the surplus in such a way that both the firm and the inventor would be better off. In that model, the bargaining power β depends on the relative dispersion of inventor and firm preferences, and the outside option of inventors depends on the variety of firms and jobs the inventor can move to. Specifically, if similar inventors are concentrated in a small number of firms, then the inventor's options are more limited.

Denote the outside option as $\omega_{ik} \equiv E[w_{ij}|\kappa(j) \neq k]$, inventor i chooses her human capital investment s_i to maximize her expected payoff:

$$s_i E[w_{ij}] - \frac{1}{2}\gamma s_i^2$$

The optimal human capital investment level is:

$$s_{ik}^* = \frac{1}{\gamma}\left((1-\beta)\omega_{ik} + \beta y_{ik}\right) \tag{9}$$

In equilibrium, we have $\omega_{ik} < y_{ik}$, otherwise the inventor would move to another firm and get higher wages. The firm's profit is surplus from the innovation minus the inventor's wage:

$$\pi_{ik} = s^*_{ik}(y_{ik} - w_{ij}) = \frac{1-\beta}{\gamma}\left((1-\beta)\omega_{ik} + \beta y_{ik}\right)(y_{ik} - \omega_{ik}) \tag{10}$$

Below, we examine the predictions of the three non-mutually-exclusive channels—labor market power, synergy, and product market power—in this framework.

Labor Market Power. When firm k merges with another firm, the options for inventors outside of the firm become more limited if the two firms compete for inventors in the same labor market. As a result, the outside option ω_{ik} decreases. The effect is larger if the labor market concentration for inventors is high and the merger has a large positive impact on labor market concentration (Jarosch et al., 2024; Caldwell and Danieli, 2024).

According to equation 9, a lower ω_{ik} leads to lower human capital investment s_{ik}, and reduces the amount of innovation developed by the inventor. The share of surplus obtained by the inventor is: $w_{ij}/y_{ik} = \beta + (1-\beta)\omega_{ik}/y_{ik}$, which decreases when ω_{ik} goes down. Inventors get lower expected wages because of two effects: lower probability of success due to lower human capital investment, and a smaller portion of the surplus conditional on success.

The impact of increased labor market power on firm profit is ambiguous as can be seen from equation 10: on the one hand, lower ω_{ik} reduces inventors' human capital investment and innovation, which hurts profits; on the other hand, lower ω_{ik} increases surplus captured by the firm conditional on successful innovation, which raises profits. Specifically, it can be shown that when bargaining power β is high or ω_{ik} is high, the second effect dominates because inventors' incentive to invest in human capital is already sufficiently strong, and lower ω_{ik} increases profits.[32] In this case, firms may merge in order to take advantage of the labor market power over inventors.

Synergy. Merger may create innovation synergy, which is captured by a decline in the cost of human capital investment γ. Therefore, when the innovations of target and acquirer firms are complementary, inventors can produce the same amount of innovation with less investment.

A decline in γ increases inventors' investment and innovation according to equation 9. It has no impact on the division of surplus, but it increases inventors' expected wage because of a higher probability of having successful innovation, and it further increases inventors' expected payoff because of lower cost of investment. Firm profit also increases, and innovation synergy may

[32] From equation 10, $\frac{\partial \pi_{ik}}{\partial \omega_{ik}} = (1-2\beta)y_{ik} - 2(1-\beta)\omega_{ik}$, which is negative when $\frac{1-2\beta}{2(1-\beta)}y_{ik} < \omega_{ik}$.

be a motivation for mergers.

Product Market Power. Merger may also change the marginal value of innovation to the firm y_{ik}. In particular, mergers between product market competitors can reduce the marginal value of innovation because merger allows the firms to internalizes the negative business-stealing externality.[33] Before a merger, firms innovate not only to improve product quality but also to compete for market share. After consolidation, innovation by one division increasingly comes at the expense of another's profits, reducing the net payoff to innovation.

As y_{ik} decreases, inventors' human capital investment and innovation also decrease according to equation 9. Inventors' expected wage is lower because of a lower probability of having successful innovation and lower total surplus upon successful innovation. Conditional on innovation and keeping the outside option ω_{ik} fixed, inventors now capture a larger fraction of the surplus since the total surplus is lower (i.e., w_{ij}/y_{ik} increases). The business-stealing effect is stronger when the two merging firms are competing in the same product market, and when the product market has higher concentration, in which case the post-merger firm faces limited competitive pressure and has lower incentives to innovate.

When merger leads to higher product market power, firm profit increases due to monopoly power even though the profit from innovation goes down in equation 10. Therefore, reduced innovation can be a byproduct of mergers targeting higher product market power.

The three channels have different predictions: while synergy predicts increased innovation, both labor market power and product market power channels predict reduced innovation following mergers. However, the labor market power channel has some distinct predictions from the product market power channel. First, while the labor market power channel predicts that inventors capture a smaller portion of the marginal surplus from their innovations, the product market power channel predicts that inventors capture a greater portion of the marginal surplus from their innovations. Second, the labor market power channel predicts the largest decline in innovation for mergers which has a large positive impact on the competition in the labor market for inventors in less competitive labor markets, whereas the product market power channel predicts the largest decline in innovation for mergers between product market rivals in concentrated product markets.

[33] Conversely, mergers may also allow firms to internalize positive knowledge spillovers and increase the marginal value of innovation, and all predictions would be exactly the opposite.

In a dynamic version of the model with multiple periods and time-varying idiosyncratic productivity shocks to firm-inventor pairs, inventors may move between firms if they receive a better outside offer from other firms. The labor market power and product market power channels also have different predictions regarding inventor mobility. If merger makes inventors' labor market more concentrated and limits their outside options, it reduces inventor separations because inventors are less likely to receive better offers from outside the firm. However, if merger reduces the marginal value of innovation, inventor separations would increase because the marginal value of innovation is relatively higher at other firms, which makes outside options more attractive for inventors.

B. Data Appendix

B.1. Calculating Text Similarity Between Patents

We leverage textual information from the patent abstract to derive meaning from the free-form, human-generated technical descriptions. Following the method used by Kelly et al. (2021) and Xue (2024), to convert unstructured text into a numerical form, we apply the Term Frequency-Inverse Document Frequency (TF-IDF) method for vectorizing each invention.[34] By applying this technique, the free-form text of a patent is transformed into a vector of TF-IDF-weighted terms. The similarity between any two patents is then calculated by measuring the cosine distance between their respective vectors, which ranges from zero (completely dissimilar) to one (identical). This vector-based approach provides an automated measure of similarity between patents, enhancing the ability to quantify the relationship between innovations. This method offers significant improvement over citation-based measures, where the connection between patents depends on the inventors' awareness of prior art and the discretion of patent examiners to cite related patents. By using TF-IDF, we eliminate the biases associated with citation practices and create a more consistent and objective measure of innovation similarity.

By constructing the textual similarity matrix, we can measure the technological linkages between any two patents. This similarity matrix captures the technological relevance between any patent pair based on their textual content. To measure innovation similarity, we define the technology stock of the target firm as its portfolio of previously filed patents prior to the merger. Similarly, the acquirer's technology stock is represented by its pre-merger patent portfolio. For each pair of patents, one from the target firm and one from the acquirer firm, we compute the text-based similarity score. We then calculate the average similarity across all such pairs, which serves as a proxy for the potential innovation substitutability between the target and acquirer firms.

[34] TF-IDF is a widely used natural language processing technique that captures the importance of terms in a document relative to a larger corpus. Specifically, TF measures how frequently a term appears in a specific patent, while IDF reflects how rare that term is across the entire corpus of patents. We apply this methodology to analyze a library of over 6 million patents. Prior to analysis, the text is pre-processed by removing stop words and normalizing tokens. The underlying assumption is that the importance of a term in a focal patent increases with its frequency within that document, while its uniqueness—i.e., its contribution to distinguishing the document from others—decreases with its frequency across the corpus. The final TF-IDF score, which is the product of TF and IDF, represents the weight of each term in the patent's description.

B.2. Merging SDC Platinum With the Census LBD Data

Failed Mergers. We identify failed mergers as those labeled with a "Pending" status in the SDC Platinum database. After identifying these deals, we match the firms involved in these transactions to the primary directory of employer businesses (SSL) and the Longitudinal Business Database (LBD) from the U.S. Census Bureau. We employ a matching process based on the firm name and location information, including street address, city, state and zip code. First, firm names and street addresses from the SDC Platinum and the Census SSL databases are cleaned and standardized to resolve inconsistencies such as abbreviations, punctuation, and formatting differences. This step involves removing extraneous characters, converting text to a consistent case format and applying standardized conventions for common terms (e.g., "Inc." vs. "Incorporated"). Second, we use standardized firm names and address data from the SDC Platinum database to directly identify corresponding entries in the Census SSL dataset. This step captures exact matches where the information aligns perfectly. Third, for records with slight discrepancies, we apply fuzzy matching algorithms to calculate similarity scores based on text alignment, identifying probable matches that are not exact but highly plausible. Overall, we are able to match about 60% of target firms and 70% of acquirer firms in failed mergers to Census businesses.

The matched targets and acquirers in failed mergers are validated using the U.S. Census LBD data, where the firm identifier remains unchanged. Next, we replicate the same procedures used in the complete merger sample to link employees of these firms to inventors by utilizing the Census Bureau's disambiguated and anonymized person identifiers, PIKs. We then match inventors from the target and acquirer firms in failed mergers to "counterfactual" inventors in firms without any M&A activity. This enables us to construct a sample of treated inventors and counterfactual inventors from failed mergers, which we use to estimate the impacts of failed mergers using the same difference-in-differences approach applied in the main analysis.

Publicly Listed Firms. To match public targets and acquirers in our sample to M&A deals from the SDC Platinum database, we implement a two-step procedure.

In the first step, we prioritize the Compustat-SSEL Bridge (CSB), which links Compustat firm identifiers (gvkeys) to Longitudinal Business Database (LBD) firm identifiers (firmids) on a yearly basis. For firms with a valid CSB match, we identify them as public and retrieve their CUSIP codes

from Compustat. These CUSIPs are then used to link LBD firmids to the corresponding targets and acquirers in the SDC deal data. All matches are manually verified using firm names to ensure accuracy.

In the second step, for the remaining unmatched firms in our sample, we apply a fuzzy matching procedure based on firm names and addresses to identify potential matches with entities in the SDC database. This procedure is similar to the one we use to match failed M&A deals from SDC to the LBD, but here we focus on completed transactions. The fuzzy matching is performed using firm names along with detailed location information—including street address, city, state, and ZIP code from the SDC and the primary directory of employer businesses (SSL). To ensure match accuracy, we require an exact match of both the standardized firm name and the standardized address (as provided by SDC) with the location of at least one establishment owned by the LBD firm.

B.3. Commuting Zone of Inventors

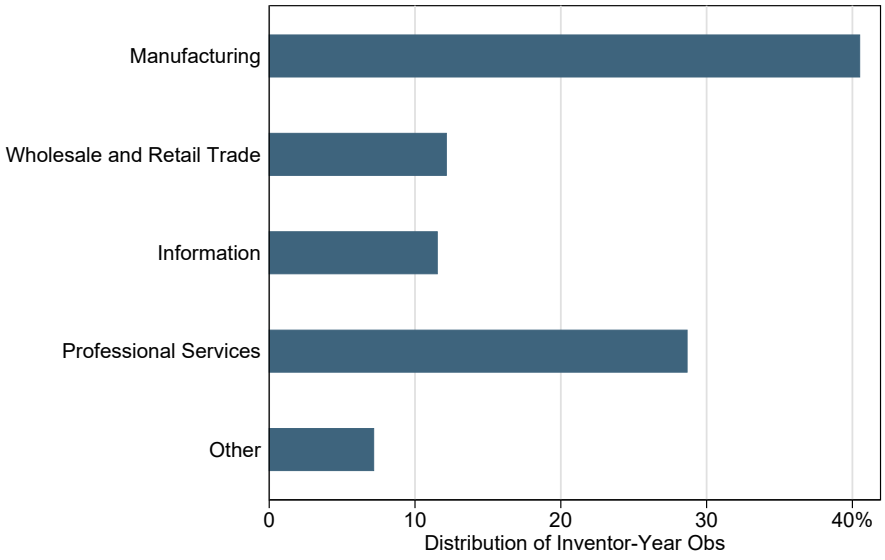
To identify each inventor's commuting zone (CZ), we rely on location information from the U.S. Census Bureau and patent filings. Inventors are required by law to report their residential location (city and state) in patent applications, which allows us to assign a CZ in years when patents are filed. For years without patent filings, we supplement this with data from the U.S. Census.

Specifically, we use Longitudinal Employer-Household Dynamics (LEHD) data to trace inventors' employment history at the state level. Using the employer's business name and state, we then consult the Longitudinal Business Database (LBD) to identify the locations of the firm's establishments within that state.

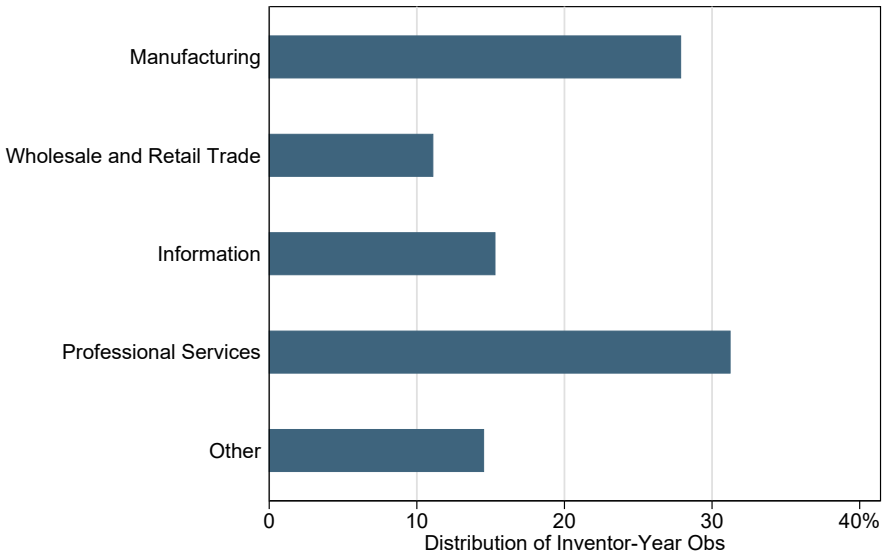
Our assignment strategy prioritizes residential information from patent filings. If an inventor has a consistent employment record with the same firm and remains in the same state, we assign the CZ based on the most recent residential location reported in patent filings. If the inventor has switched to a new employer within the same state and has no patent filings with the new firm, we still assign the CZ based on the most recent known residential location, given most in-state job changes involve local moves. If the inventor has changed employers and moved to a different state without subsequent patent filings, we infer the CZ based on the firm's establishment locations: if the firm operates in only one CZ within the state, we assign that CZ to the inventor; if it operates in multiple CZs, we assign the one with the largest number of employees.

C. Additional Tables and Figures

Figure A1: Distribution of Inventors by Industry Sector



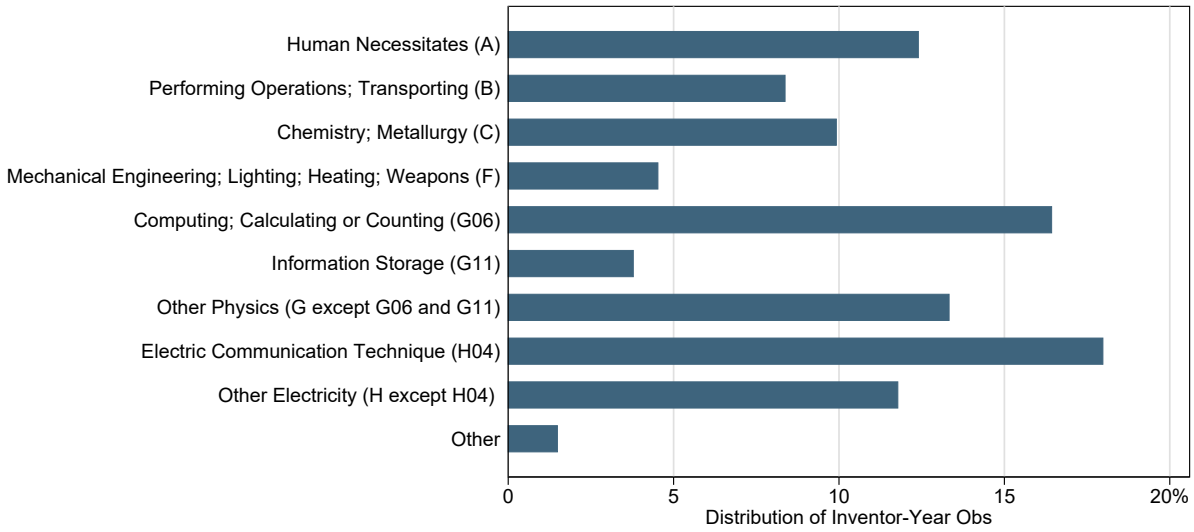
(a) Target Inventors



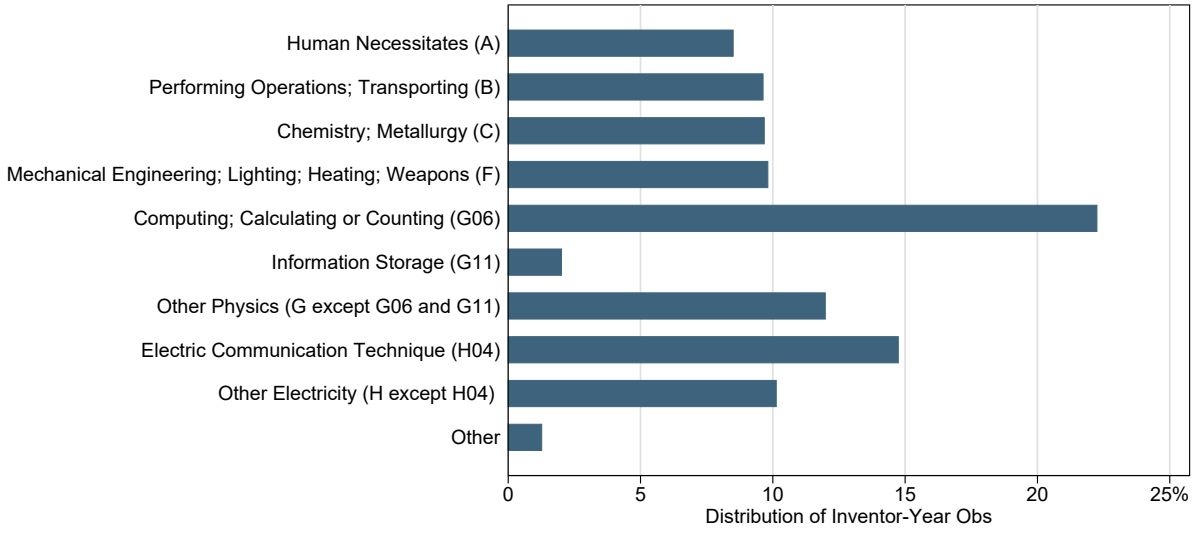
(b) Acquirer Inventors

This figure plots the distribution of inventors in our sample by industry sectors. Panel (a) plots the distribution of target inventors and Panel (b) plots the distribution of acquirer inventors. Each panel plots the percentage of inventor-year observations in the following sectors: Manufacturing (2-digit NAICS=31, 32, 33), Wholesale and Retail Trade (2-digit NAICS=42, 44, 45), Information (2-digit NAICS=51), Professional Services (2-digit NAICS=54), and other sectors.

Figure A2: Distribution of Inventors by Technological Field



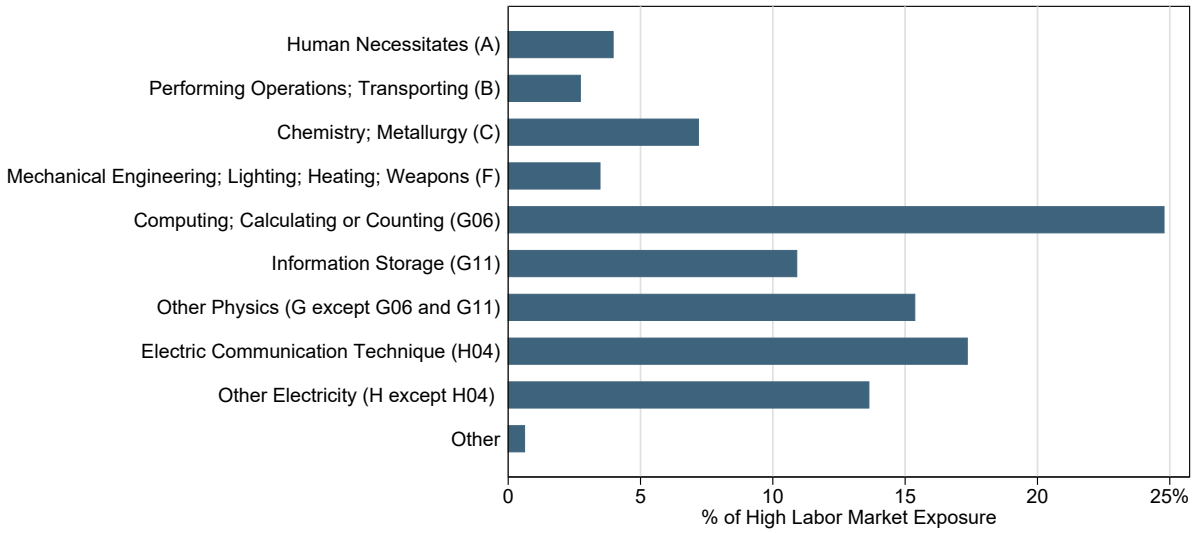
(a) Target Inventors



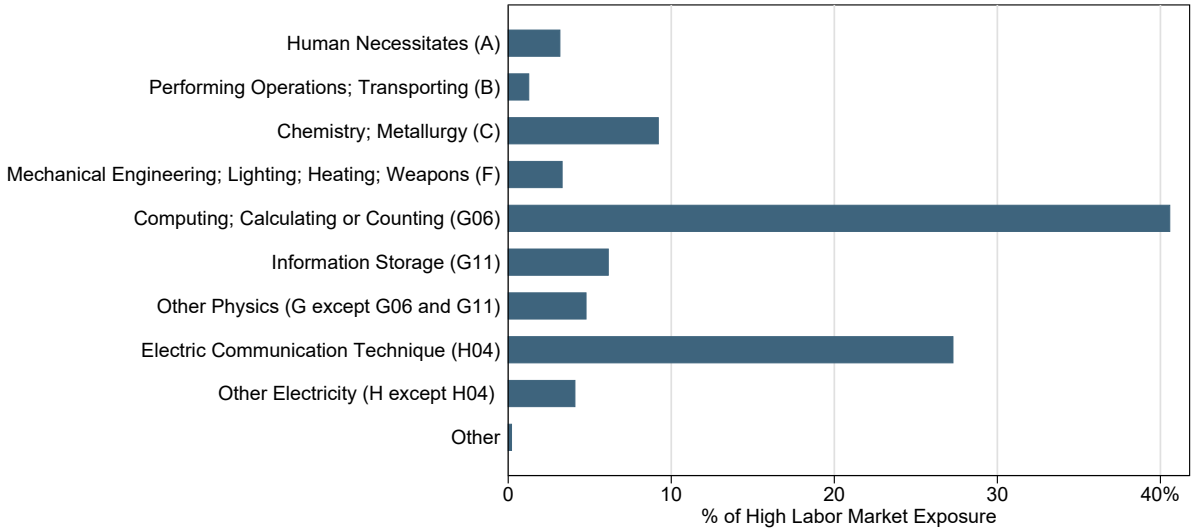
(b) Acquirer Inventors

This figure plots the distribution of inventors in our sample by technological fields. Each inventor is assigned to a primary field based on the area in which they filed the most patents during the five years preceding the merger. Panel (a) plots the distribution of target inventors and Panel (b) plots the distribution of acquirer inventors. Each panel plots the percentage of inventor-year observations in the following technological fields: Human Necessitates (CPC section A), Performing Operations; Transporting (CPC section B), Chemistry; Metallurgy (CPC section C), Mechanical Engineering; Lighting; Heating; Weapons (CPC section F), Computing; Calculating or Counting (CPC class G06), Information Storage (CPC class G11), Other Physics (CPC section G and CPC class is not G06 or G11), Electric Communication Technique (CPC class H04), Other Electricity (CPC section H and CPC class is not H04), and other fields.

Figure A3: Distribution of High-Labor-Market-Exposure Inventors by Technological Field



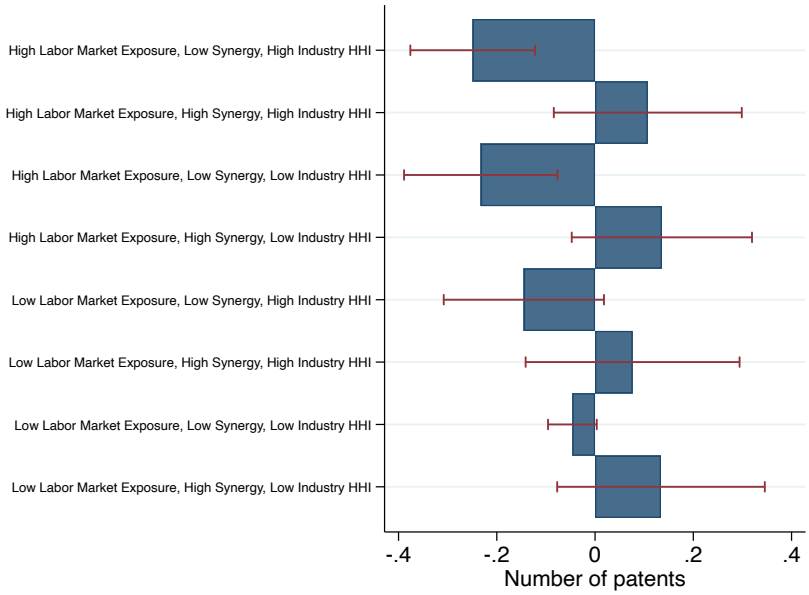
(a) Target Inventors



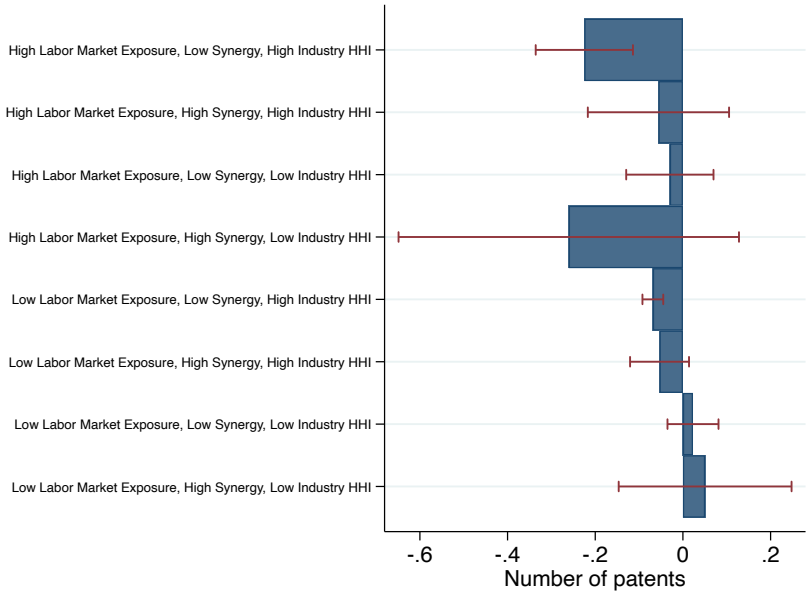
(b) Acquirer Inventors

This figure plots the distribution of high-labor-market-exposure inventors in our sample by technological fields. Each inventor is assigned to a primary field based on the area in which they filed the most patents during the five years preceding the merger. Panel (a) plots the distribution of target inventors and Panel (b) plots the distribution of acquirer inventors. Each panel plots the percentage of inventor-year observations in the following technological fields: Human Necessitates (CPC section A), Performing Operations; Transporting (CPC section B), Chemistry; Metallurgy (CPC section C), Mechanical Engineering; Lighting; Heating; Weapons (CPC section F), Computing; Calculating or Counting (CPC class G06), Information Storage (CPC class G11), Other Physics (CPC section G and CPC class is not G06 or G11), Electric Communication Technique (CPC class H04), Other Electricity (CPC section H and CPC class is not H04), and other fields.

Figure A4: Changes in the Number of Patents around M&As by Exposure to Labor Market Impact, Synergy, and Industry Concentration



(a) Target Inventors



(b) Acquirer Inventors

This figure plots difference-in-differences estimates and 95% confidence intervals for the effect of M&As on the number of patents for each of the eight inventor groups split by whether an inventor experiences high or low exposure to the labor-market-power impact of a merger, whether the merger has high or low innovation synergy, and whether the acquirer or target firm is in a high-HHI or low-HHI industry. Panel (a) shows the estimates for target inventors and Panel (b) shows the estimates for acquirer inventors.

Table A1: Distribution of High Exposure Inventors by Target Firm Size and Age Quintiles

By Firm Employment	Fraction
Quintile 1	12.84%
Quintile 2	11.93%
Quintile 3	25.69%
Quintile 4	25.69%
Quintile 5	23.85%

By Firm Age	Fraction
Quintile 1	14.81%
Quintile 2	22.22%
Quintile 3	31.48%
Quintile 4	18.52%
Quintile 5	12.96%

This table reports the distribution of high labor market exposure inventors at target firms. The top panel presents the distribution across firm size quintiles, where firm size is measured by employment, while the bottom panel presents the distribution across firm age quintiles. Firm size and age quintiles are calculated based on the sample of all target firm inventors. All statistics and observation counts are rounded in accordance with U.S. Census Bureau disclosure requirements.

Table A2: Changes in Returns to Patenting around M&As: Earnings Levels

Panel A: Weighted by Citation

	Annual Earnings (Thousands)					
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted Patents 1 Year	1.513***	-0.1515				
	(0.0861)	(0.1421)				
Weighted Patents 1 Year × Post × High Exposure		-1.692***				
		(0.5134)				
Weighted Patents 2 Year			1.343***	0.2028*		
			(0.0734)	(0.1135)		
Weighted Patents 2 Year × Post × High Exposure				-1.202***		
				(0.3472)		
Weighted Patents 3 Year					1.244***	0.3690***
					(0.0657)	(0.0968)
Weighted Patents 3 Year × Post × High Exposure						-0.8661***
						(0.2710)
Obs	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000

Panel B: Weighted by Economic Value

	Annual Earnings (Thousands)					
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted Patents 1 Year	1.645***	0.0241				
	(0.0892)	(0.1452)				
Weighted Patents 1 Year × Post × High Exposure		-0.7244				
		(0.4712)				
Weighted Patents 2 Year			1.658***	0.5277***		
			(0.0727)	(0.1049)		
Weighted Patents 2 Year × Post × High Exposure				-0.9314***		
				(0.3018)		
Weighted Patents 3 Year					1.584***	0.7833***
					(0.0635)	(0.0839)
Weighted Patents 3 Year × Post × High Exposure						-0.9004***
						(0.2270)
Obs	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000	1,660,000

This table reports the regression estimates from model 5. The dependent variable is annual earnings (in thousands of dollars). *Weighted Patents 1 Year* (*2 Years*, or *3 Years*) refers to the count of patents weighted by normalized citations (in Panel A) or economic value (in Panel B) that are granted within the preceding one (two, or three) years. The citations are normalized by patent technology class and grant year. The economic value of patents is measured using excess stock market returns following Kogan et al. (2017). The *Post* dummy indicates the years after the M&A event. The *High Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The sample contains all observations of treated inventors in target or acquirer firms. All regressions control for two-way interactions between weighted patent counts, the *Post* dummy, and the *High Labor Market Exposure* dummy. All regressions also include inventor-firm fixed effects and year fixed effects. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A3: Alternative Synergy Measures

	Target Inventors			Acquirer Inventors		
	Number of Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0477*	-0.0534*	-0.0489*	-0.0561**	-0.0525*	-0.0546**
	(0.0258)	(0.0299)	(0.0262)	(0.0262)	(0.0275)	(0.0268)
Post × High Text Similarity	-0.0815	-0.1039	-0.0470	0.0253	0.0622	0.0291
	(0.0791)	(0.0964)	(0.0625)	(0.0564)	(0.0551)	(0.0711)
Post × High Complementarity × High Text Similarity	-0.0563			0.0146		
	(0.0944)			(0.0540)		
Post × High Complementarity × Low Text Similarity	0.1606**			0.0225		
	(0.0679)			(0.0532)		
Post × High Technology Proximity × High Text Similarity		-0.0055			-0.0413	
		(0.1053)			(0.0530)	
Post × High Technology Proximity × Low Text Similarity		0.0932*			0.0035	
		(0.0527)			(0.0484)	
Post × High Knowledge Base Overlap × High Text Similarity			-0.0963			0.0060
			(0.0821)			(0.0688)
Post × High Knowledge Base Overlap × Low Text Similarity			0.0919			0.0134
			(0.0647)			(0.0512)
Obs	160,000	160,000	160,000	2,210,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes using alternative measures of innovation synergy. The dependent variable is the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor. Columns 1–3 show the estimates for target inventors and columns 4–6 show the estimates for acquirer inventors. The *Post* dummy indicates the years after the M&A event. The *High (Low) Text Similarity* dummy indicates above-median (below-median) innovation substitutability based on textual similarity between the target's and the acquirer's patents. The *High Technology Proximity* dummy indicates above-median cosine similarity in the merging firms' innovation activities in technology space, measured using patent counts across technology classes, following Jaffe (1986). The *High Knowledge Base Overlap* dummy indicates above-median number of patents in the common knowledge base, defined as the set of patents cited at least once by both the acquirer's and the target's patents with grant years from $t-5$ to $t-1$, following Bena and Li (2014). The *High Complementarity* dummy equals one if both the *High Technology Proximity* and *High Knowledge Base Overlap* dummies equal one. We control for the *Pre* dummy indicating pre-merger periods, the alternative measures of merger synergy, and their interactions with the *Pre* dummy in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A4: Changes in Inventors' Normalized Earnings around M&As

	Target Inventors		Acquirer Inventors	
	Normalized Earnings			
	(1)	(2)	(3)	(4)
Post	-0.0128	0.0015	-0.0437***	-0.0376**
	(0.0157)	(0.0236)	(0.0075)	(0.0184)
Post × High Labor Market Exposure	-0.0379*	-0.0399*	-0.0545***	-0.0554***
	(0.0227)	(0.0209)	(0.0163)	(0.0157)
Post × High Synergy		-0.0975**		-0.0388*
		(0.0435)		(0.0206)
Post × High Text Similarity		0.0110		-0.0051
		(0.0339)		(0.0169)
Post × High Industry Concentration		-0.0351		0.0089
		(0.0299)		(0.0153)
Post × Horizontal		-0.0141		-0.0209
		(0.0258)		(0.0196)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' normalized earnings based on equation 3. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference between the treated inventor's annual earnings (normalized by the annual earnings in year $t-1$) and the matched counterfactual inventor's annual earnings (normalized by the annual earnings in year $t-1$). The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A5: Changes in Inventors' Departures to Entrepreneurship around M&As

	Target Inventors		Acquirer Inventors	
	Entrepreneurship Dummy			
	(1)	(2)	(3)	(4)
Post	0.0006	0.0010	-0.0032***	-0.0028***
	(0.0055)	(0.0058)	(0.0006)	(0.0011)
Post × High Labor Market Exposure	-0.0140*	-0.0082*	-0.0022**	-0.0022**
	(0.0074)	(0.0045)	(0.0010)	(0.0010)
Post × High Synergy		-0.0144*		0.0010
		(0.0086)		(0.0029)
Post × High Text Similarity		-0.0140		-0.0009
		(0.0098)		(0.0012)
Post × High Industry Concentration		0.0113		-0.0003
		(0.0086)		(0.0012)
Post × Horizontal		0.0127		0.0007
		(0.0080)		(0.0015)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' departures to entrepreneurship based on equation 3. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference in entrepreneurship between the treated inventor and the matched counterfactual inventor. The entrepreneurship dummy equals one if the inventor founds a new firm, defined as working at a firm in the year it is founded, where that firm differs from the inventor's employer in year $t-1$. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A6: Changes in Inventor Outcomes around M&As Controlling for Event-Firm-Year Fixed Effects

Panel A: Target Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0417	0.1553	0.0512	0.0070	0.1189*	0.2829***
	(0.0777)	(0.1932)	(0.0389)	(0.0548)	(0.0721)	(0.0934)
Post × High Labor Market Exposure	-0.1257**	-0.1211**	-0.0340*	-0.0247	-0.0335	-0.0341*
	(0.0585)	(0.0589)	(0.0181)	(0.0170)	(0.0204)	(0.0199)
Event×Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	160,000	160,000	160,000	160,000	96,000	96,000

Panel B: Acquirer Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0284**	0.0091	-0.0047	0.0383	-0.1821***	-0.1818***
	(0.0131)	(0.0269)	(0.0102)	(0.0241)	(0.0088)	(0.0210)
Post × High Labor Market Exposure	-0.0525*	-0.0590**	-0.0292***	-0.0320***	-0.0203	-0.0197*
	(0.0275)	(0.0279)	(0.0101)	(0.0107)	(0.0125)	(0.0118)
Event×Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2,210,000	2,210,000	2,210,000	2,210,000	1,353,000	1,353,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes controlling for event-firm-year fixed effects. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 2, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 3 and 4, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 5 and 6. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A7: Changes in Inventor Outcomes around M&As Controlling for Event-Firm-CZ-Year Fixed Effects

Panel A: Target Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0762	0.1426	0.0657	0.0343	0.1044	0.3148***
	(0.0909)	(0.2210)	(0.0445)	(0.0660)	(0.0723)	(0.1005)
Post × High Labor Market Exposure	-0.1092	-0.1058	-0.0237	-0.0132	-0.0064	-0.0065
	(0.0698)	(0.0708)	(0.0229)	(0.0216)	(0.0170)	(0.0153)
Event×Firm×CZ×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	160,000	160,000	160,000	160,000	96,000	96,000

Panel B: Acquirer Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0105	0.0228	-0.0038	0.0421*	-0.1861***	-0.1934***
	(0.0133)	(0.0267)	(0.0108)	(0.0255)	(0.0089)	(0.0200)
Post × High Labor Market Exposure	-0.0467*	-0.0533*	-0.0258**	-0.0289**	-0.0223*	-0.0206*
	(0.0279)	(0.0284)	(0.0108)	(0.0114)	(0.0132)	(0.0124)
Event×Firm×CZ×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2,210,000	2,210,000	2,210,000	2,210,000	1,353,000	1,353,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes controlling for event-firm-commuting-zone-year fixed effects. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 2, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 3 and 4, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 5 and 6. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p <$ 0.01, **$p < 0.05$, *$p < 0.1$, respectively).

Table A8: Matching Treated Inventors to Counterfactual Inventors in the Same 3-digit Technological Field

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0677	-0.0069	0.0462*
	(0.0538)	(0.0284)	(0.0278)
Post × High Labor Market Exposure	-0.1591**	-0.0450**	-0.0724***
	(0.0687)	(0.0226)	(0.0239)
Post × High Synergy	0.2424**	-0.0780*	-0.0023
	(0.0992)	(0.0457)	(0.0652)
Post × High Text Similarity	-0.0515	0.0169	-0.0614*
	(0.0644)	(0.0355)	(0.0362)
Post × High Industry Concentration	-0.0779	-0.0309	0.0346
	(0.0748)	(0.0308)	(0.0378)
Post × Horizontal	-0.0340	-0.0254	-0.0029
	(0.0612)	(0.0307)	(0.0343)
Obs	104,000	104,000	62,500

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0216	-0.0092	-0.1117***
	(0.0506)	(0.0236)	(0.0180)
Post × High Labor Market Exposure	-0.1121***	-0.0398**	-0.0589***
	(0.0435)	(0.0161)	(0.0187)
Post × High Synergy	0.0259	-0.0696***	0.0834***
	(0.0822)	(0.0233)	(0.0285)
Post × High Text Similarity	0.0456	-0.0196	0.0465**
	(0.0466)	(0.0196)	(0.0198)
Post × High Industry Concentration	-0.0952**	-0.0006	-0.0208
	(0.0427)	(0.0165)	(0.0188)
Post × Horizontal	-0.0523	-0.0395**	0.0133
	(0.0477)	(0.0172)	(0.0190)
Obs	1,381,000	1,381,000	848,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes where we match treated inventors to counterfactual inventors with the same primary 3-digit technological field. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The independent variables and controls are the same as in Table 4. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A9: Matching Treated Inventors to Counterfactual Inventors in the Same 4-digit Technological Field

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0923	0.0000	0.0621**
	(0.0692)	(0.0367)	(0.0310)
Post × High Labor Market Exposure	-0.1513*	-0.0477*	-0.0754**
	(0.0857)	(0.0276)	(0.0295)
Post × High Synergy	0.3523***	-0.0566	X
	(0.1133)	(0.0532)	
Post × High Text Similarity	-0.0428	0.0250	-0.0627
	(0.0797)	(0.0421)	(0.0387)
Post × High Industry Concentration	-0.1474	-0.0698*	0.0397
	(0.1039)	(0.0362)	(0.0410)
Post × Horizontal	-0.0313	-0.0478	-0.0328
	(0.0784)	(0.0354)	(0.0371)
Obs	73,500	73,500	44,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0137	-0.0215	-0.1344***
	(0.0526)	(0.0213)	(0.0234)
Post × High Labor Market Exposure	-0.1117**	-0.0243	-0.0413*
	(0.0551)	(0.0181)	(0.0221)
Post × High Synergy	-0.0196	-0.0864***	0.0876**
	(0.1027)	(0.0272)	(0.0360)
Post × High Text Similarity	0.0189	-0.0230	0.0501**
	(0.0573)	(0.0224)	(0.0241)
Post × High Industry Concentration	-0.0650	-0.0075	-0.0114
	(0.0520)	(0.0190)	(0.0227)
Post × Horizontal	-0.0667	-0.0017	0.0162
	(0.0572)	(0.0231)	(0.0219)
Obs	940,000	940,000	577,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes where we match treated inventors to counterfactual inventors with the same primary 4-digit technological field. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The independent variables and controls are the same as in Table 4. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively). Cells marked "X" indicate estimates suppressed under Census disclosure rules.

Table A10: Splitting Inventors by Labor Market Exposure within Technological Fields

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0751**	-0.0245*	0.0273
	(0.0315)	(0.0130)	(0.0172)
Post × High Labor Market Exposure	-0.0908*	-0.0145	-0.1060***
	(0.0520)	(0.0232)	(0.0280)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0242	-0.0300***	-0.0755***
	(0.0149)	(0.0058)	(0.0091)
Post × High Labor Market Exposure	-0.0843**	-0.0314**	-0.0271***
	(0.0378)	(0.0152)	(0.0086)
Obs	160,000	160,000	96,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes, where we split inventors by labor market exposure within technological fields. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration, where the median of the predicted change in HHI is calculated separately for each 4-digit technological field. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the M&A event. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A11: Rising vs. Declining Technological Fields

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0617**	-0.0187	0.0281
	(0.0288)	(0.0131)	(0.0185)
Post × High Labor Market Exposure × Low Growth Field	-0.1348	-0.0192	-0.0604**
	(0.1066)	(0.0228)	(0.0250)
Post × High Labor Market Exposure × High Growth Field	-0.1433**	-0.0549*	-0.1188***
	(0.0660)	(0.0307)	(0.0360)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0232	-0.0310***	-0.0832***
	(0.0152)	(0.0062)	(0.0074)
Post × High Labor Market Exposure × Low Growth Field	0.0120	-0.0263	-0.0314*
	(0.0463)	(0.0241)	(0.0175)
Post × High Labor Market Exposure × High Growth Field	-0.1268***	-0.0311*	-0.0423**
	(0.0467)	(0.0169)	(0.0176)
Obs	2,210,000	2,210,000	1,353,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes in rising vs. declining technological fields. The *Low (High) Growth Field* dummy indicates that the 4-digit technological field has below-median (above-median) growth in the number of patents from five years before the merger to one year before the merger. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, the *High Growth Field* and *Low Growth Field* dummies, and their interaction in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A12: Controlling for National Innovation Market Exposure

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0199	-0.0062	0.0624***
	(0.0353)	(0.0190)	(0.0237)
Post × High Labor Market Exposure	-0.1392**	-0.0527**	-0.0582**
	(0.0649)	(0.0262)	(0.0246)
Post × High National Innovation Market Exposure	0.0107	0.0232	-0.0162
	(0.0630)	(0.0288)	(0.0287)
Post × High Synergy	0.1911**	-0.0667**	-0.0099
	(0.0745)	(0.0337)	(0.0498)
Post × High Text Similarity	-0.0844	0.0029	-0.0786**
	(0.0535)	(0.0263)	(0.0319)
Post × High Industry Concentration	-0.0787	-0.0179	0.0463
	(0.0673)	(0.0242)	(0.0348)
Post × Horizontal	0.0204	-0.0207	-0.0184
	(0.0480)	(0.0230)	(0.0310)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	0.0183	-0.0142	-0.0992***
	(0.0342)	(0.0156)	(0.0150)
Post × High Labor Market Exposure	-0.0754*	-0.0285**	-0.0238*
	(0.0394)	(0.0122)	(0.0135)
Post × High National Innovation Market Exposure	-0.0515	-0.0115	-0.0210**
	(0.0361)	(0.0078)	(0.0094)
Post × High Synergy	0.0355	-0.0471**	0.0642***
	(0.0507)	(0.0183)	(0.0241)
Post × High Text Similarity	0.0416	-0.0104	0.0329**
	(0.0326)	(0.0141)	(0.0154)
Post × High Industry Concentration	-0.1064***	0.0032	-0.0128
	(0.0312)	(0.0126)	(0.0147)
Post × Horizontal	-0.0277	-0.0272*	0.0061
	(0.0351)	(0.0160)	(0.0182)
Obs	2,210,000	2,210,000	1,353,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes controlling for national innovation market exposure. The *High National Innovation Market Exposure* dummy indicates that the merger has an above-median predicted impact on concentration in an innovation market with above-median initial level of concentration, where innovation market concentration is calculated using national market shares of inventors within each technology class. Other independent variables and control variables are defined as in Table 4. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A13: Changes in Inventor Outcomes around Failed Mergers

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0271	-0.0162	-0.0173
	(0.0371)	(0.0224)	(0.0443)
Post × High Labor Market Exposure	-0.0234	0.0143	-0.0447
	(0.0491)	(0.0193)	(0.0459)
Obs	100,000	100,000	61,500

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0467**	0.0137	-0.0873***
	(0.0209)	(0.0148)	(0.0158)
Post × High Labor Market Exposure	0.2472	-0.0257	-0.0195
	(0.1907)	(0.0220)	(0.0415)
Obs	434,000	434,000	262,000

This table reports difference-in-differences estimates of the effect of failed mergers (mergers that were announced but never completed) on inventors outcomes. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 2, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 3 and 4, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 5 and 6. The *Post* dummy indicates the years after the announcement of the failed merger. The *High Labor Market Exposure* dummy indicates that the failed merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A14: Change in the Number of Patents around Spinoffs

	All Inventors	Parent Firm Inventors	Spun-off Firm Inventors
	(1)	(2)	(3)
Post	-0.0416**	-0.0423*	-0.0405
	(0.0210)	(0.0253)	(0.0367)
Post × High Labor Market Exposure	0.0453	0.0422	0.0866
	(0.0398)	(0.0440)	(0.1133)
Obs	125,000	96,000	29,000

This table reports difference-in-differences estimates of the effect of spinoffs on the number of patents. The dependent variable is the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in a given year. Column 1 shows the estimates for all inventors employed at the parent firm in year $t-1$. Column 2 shows the estimates for inventors who remain with the parent firm in year 0. Column 3 shows the estimates for inventors who move to work at the spun-off firms in year 0. The *Post* dummy indicates the years after the spinoff event. The *High Labor Market Exposure* dummy indicates that the spinoff has an above-median predicted negative impact on the labor market concentration of the inventor. We control for the *Pre* dummy indicating pre-spinoff periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A15: Heterogeneous Effects of M&As on Inventors by Pre-merger Inventor Characteristics

	Target Inventors			Acquirer Inventors		
	Number of Patents	Log Annual Earnings	Separation Rate	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Post × High Labor Market Exposure × Inventor Age	-0.0049	0.0001	0.0001	0.0049**	-0.0023**	0.0009
	(0.0042)	(0.0013)	(0.0015)	(0.0021)	(0.0010)	(0.0008)
Post × High Labor Market Exposure × Job Tenure	-0.0081	-0.0014	0.0080***	0.0220***	-0.0020	0.0026
	(0.0072)	(0.0028)	(0.0030)	(0.0055)	(0.0016)	(0.0019)
Post × High Labor Market Exposure × Inventor Productivity	-0.1978***	-0.0203	0.0171	-0.0470	0.0064	-0.0042
	(0.0746)	(0.0134)	(0.0137)	(0.0552)	(0.0070)	(0.0067)
Post × High Labor Market Exposure × Log Annual Earnings	-0.0882	-0.0470	0.0285	-0.0886*	-0.0109	0.0093
	(0.0670)	(0.0363)	(0.0244)	(0.0498)	(0.0290)	(0.0140)
Post × High Labor Market Exposure × Total Citations	-0.0545	-0.0059	0.0128	-0.0273	0.0069*	-0.0033
	(0.0410)	(0.0076)	(0.0093)	(0.0273)	(0.0039)	(0.0045)
Obs	160,000	160,000	96,000	2,210,000	2,210,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes by pre-merger inventor characteristics. Each cell is a separate regression. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 4, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 2 and 5, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 4 and 6. Columns 1–3 show the estimates for target inventors and columns 4–6 show the estimates for acquirer inventors. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The key independent variable is the triple interaction between the *Post* dummy, the *High Labor Market Exposure* dummy, and inventor characteristics measured before the merger. Inventor age, job tenure, and log annual earnings are measured in year -1. Inventor productivity is the total number of patents filed during the five years before the merger. Total citations are the total number of citations received by the patents filed in the five years before the merger. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, inventor characteristics, the interaction between the *Pre* dummy and the *High Labor Market Exposure* dummy, the interaction between the *Post* dummy and the *High Labor Market Exposure* dummy, the interaction between inventor characteristic and the *Pre* dummy, the interaction between inventor characteristic and the *High Labor Market Exposure* dummy, and the interaction between inventor characteristic and the *Post* dummy in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A16: Heterogeneous Effects of M&As on Inventors by Pre-merger Firm Characteristics

	Target Inventors			Acquirer Inventors		
	Number of Patents	Log Annual Earnings	Separation Rate	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Post × High Labor Market Exposure × Target Size	-0.0245	-0.0157**	-0.0056	0.0191	-0.0049	-0.0037
	(0.0237)	(0.0077)	(0.0140)	(0.0161)	(0.0086)	(0.0059)
Post × High Labor Market Exposure × Acquirer Size	0.0341***	0.0094**	0.0078	0.0345	-0.0063	-0.0090
	(0.0109)	(0.0044)	(0.0060)	(0.0213)	(0.0084)	(0.0096)
Post × High Labor Market Exposure × Target Age	-0.0091**	-0.0013	0.0014	0.0040	-0.0015	0.0007
	(0.0039)	(0.0013)	(0.0018)	(0.0026)	(0.0011)	(0.0011)
Post × High Labor Market Exposure × Acquirer Age	0.0083*	0.0032**	0.0022	0.0225***	-0.0009	-0.0023
	(0.0043)	(0.0012)	(0.0017)	(0.0038)	(0.0019)	(0.0015)
Post × High Labor Market Exposure × Public Target	-0.0803	-0.0713**	-0.0529	-0.0248	-0.0205	-0.0238
	(0.0888)	(0.0292)	(0.0459)	(0.0705)	(0.0266)	(0.0291)
Post × High Labor Market Exposure × Public Acquirer	0.0377	-0.0494	-0.0513	0.0265	-0.0560**	-0.0143
	(0.0802)	(0.0395)	(0.0492)	(0.0910)	(0.0266)	(0.0347)
Obs	160,000	160,000	96,000	2,210,000	2,210,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes by pre-merger firm characteristics. Each cell is a separate regression. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 4, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 2 and 5, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 4 and 6. Columns 1–3 show the estimates for target inventors and columns 4–6 show the estimates for acquirer inventors. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The key independent variable is the triple interaction between the *Post* dummy, the *High Labor Market Exposure* dummy, and firm characteristics measured before the merger. Target/acquirer size is measured by log employment in year -1. Target/acquirer age is measured by the age of the oldest establishment of a firm in year -1. Public target/acquirer is dummy indicating whether the acquirer or target firm is publicly listed in year -1. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, firm characteristics, the interaction between the *Pre* dummy and the *High Labor Market Exposure* dummy, the interaction between the *Post* dummy and the *High Labor Market Exposure* dummy, the interaction between firm characteristic and the *Pre* dummy, the interaction between firm characteristic and the *High Labor Market Exposure* dummy, and the interaction between firm characteristic and the *Post* dummy in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A17: Effects of M&As on Inventors When the Acquirer Firm is Public

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	0.0141	-0.0114	0.0495*
	(0.0461)	(0.0251)	(0.0297)
Post × High Labor Market Exposure	-0.1622**	-0.0400*	-0.0903***
	(0.0797)	(0.0220)	(0.0254)
Post × High Synergy	0.1784*	-0.0759	X
	(0.1001)	(0.0542)	
Post × High Text Similarity	-0.1295*	-0.0274	-0.0529
	(0.0689)	(0.0348)	(0.0503)
Post × High Industry Concentration	-0.1023	-0.0138	0.0581
	(0.0894)	(0.0303)	(0.0493)
Post × Horizontal	0.0178	0.0159	-0.0450
	(0.0774)	(0.0327)	(0.0423)
Obs	95,500	95,500	57,500

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	0.0319	-0.0147	-0.1212***
	(0.0393)	(0.0177)	(0.0156)
Post × High Labor Market Exposure	-0.1216***	-0.0361***	-0.0332**
	(0.0381)	(0.0132)	(0.0143)
Post × High Synergy	0.0346	-0.0554***	0.0610***
	(0.0554)	(0.0201)	(0.0226)
Post × High Text Similarity	0.0466	-0.0122	0.0407**
	(0.0361)	(0.0157)	(0.0164)
Post × High Industry Concentration	-0.1263***	0.0060	-0.0024
	(0.0354)	(0.0142)	(0.0157)
Post × Horizontal	-0.0235	-0.0264	0.0072
	(0.0386)	(0.0180)	(0.0197)
Obs	1,978,000	1,978,000	1,212,000

This table reports difference-in-differences estimates of the effect of M&As on inventor outcomes for the subsample where the acquirer firm is publicly listed. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The independent variables and controls are the same as in Table 4. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A18: Effects of M&As on Inventors by Initial Level and Change in Labor Market Concentration

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	0.0123	-0.0135	0.0483**
	(0.0368)	(0.0119)	(0.0190)
Post × Low Initial HHI × High ΔHHI	-0.1745***	-0.0010	-0.0437*
	(0.0651)	(0.0257)	(0.0257)
Post × High Initial HHI × Low ΔHHI	-0.0525	-0.0104	-0.0215
	(0.0461)	(0.0141)	(0.0273)
Post × High Initial HHI × High ΔHHI	-0.2130***	-0.0448*	-0.1074***
	(0.0731)	(0.0247)	(0.0312)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0168	-0.0243***	-0.0746***
	(0.0216)	(0.0077)	(0.0092)
Post × Low Initial HHI × High ΔHHI	-0.0210	-0.0061	0.0204
	(0.0356)	(0.0164)	(0.0165)
Post × High Initial HHI × Low ΔHHI	-0.0131	-0.0087	-0.0293***
	(0.0199)	(0.0068)	(0.0080)
Post × High Initial HHI × High ΔHHI	-0.0834*	-0.0466***	-0.0536***
	(0.0428)	(0.0128)	(0.0160)
Obs	160,000	160,000	96,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes by initial labor market concentration and its predicted change defined in equation 2. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the M&A event. The *High (Low) Initial HHI* dummy indicates whether the treated inventor is in labor markets with above-median (below-median) initial concentration prior to the merger. The *High (Low)* Δ*HHI* dummy indicates whether the merger has an above-median (below-median) predicted impact on the labor market concentration for the treated inventor. We control for the *Pre* dummy indicating pre-merger periods, the *High Initial HHI* dummy, the *High* Δ*HHI* dummy, and all of their two-way interactions in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A19: Effects of M&As on Inventors By Quartile of Change in Labor Market Concentration

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0639**	-0.0181	0.0277*
	(0.0285)	(0.0121)	(0.0144)
Post × High Initial HHI × ΔHHI Quartile 1	0.0338	-0.0078	0.0184
	(0.0437)	(0.0198)	(0.0330)
Post × High Initial HHI × ΔHHI Quartile 2	-0.0338	0.0035	0.0019
	(0.0623)	(0.0325)	(0.0336)
Post × High Initial HHI × ΔHHI Quartile 3	-0.1199*	-0.0342	-0.0513
	(0.0700)	(0.0252)	(0.0343)
Post × High Initial HHI × ΔHHI Quartile 4	-0.1829*	-0.0492*	-0.1059***
	(0.1082)	(0.0294)	(0.0406)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0214	-0.0211***	-0.0503***
	(0.0169)	(0.0072)	(0.0092)
Post × High Initial HHI × ΔHHI Quartile 1	-0.0090	-0.0122	0.0137
	(0.0361)	(0.0128)	(0.0177)
Post × High Initial HHI × ΔHHI Quartile 2	-0.0697	-0.0367	-0.0531*
	(0.0654)	(0.0218)	(0.0291)
Post × High Initial HHI × ΔHHI Quartile 3	-0.0950	-0.0332*	-0.0780***
	(0.0627)	(0.0178)	(0.0224)
Post × High Initial HHI × ΔHHI Quartile 4	-0.1027*	-0.0500***	-0.1039***
	(0.0600)	(0.0173)	(0.0201)
Obs	160,000	160,000	96,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes by quartile of change in labor market concentration defined in equation 2. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the M&A event. The *High Initial HHI* dummy indicates whether the treated inventor is in labor markets with above-median initial concentration prior to the merger. The Δ*HHI Quartile 1 (2/3/4)* dummy indicates whether the predicted impact on the labor market concentration for the treated inventor falls into quartile 1 (2/3/4). We control for the *Pre* dummy indicating pre-merger periods, the *High Initial HHI* dummy, the Δ*HHI Quartile 1 (2/3/4)* dummies, and their interactions in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A20: Effects of M&As on High-Labor-Market-Exposure Inventors Using Alternative Labor Market Concentration Measures

Panel A: Using 3-Digit CPC Technology Class.

	Target Inventors			Acquirer Inventors		
	Number of Patents	Log Annual Earnings	Separation Rate	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0185	-0.0044	0.0630***	0.0018	-0.0179	-0.1001***
	(0.0357)	(0.0194)	(0.0232)	(0.0359)	(0.0161)	(0.0148)
Post × High Labor Market Exposure	-0.1472***	-0.0438**	-0.0795***	-0.0446	-0.0363***	-0.0629***
	(0.0475)	(0.0180)	(0.0260)	(0.0321)	(0.0122)	(0.0147)
Obs	160,000	160,000	96,000	2,210,000	2,210,000	1,350,000

Panel B: 1% Threshold for Geographical Markets.

	Target Inventors			Acquirer Inventors		
	Number of Patents	Log Annual Earnings	Separation Rate	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0260	-0.0121	0.0533**	0.0054	-0.0231	-0.1061***
	(0.0390)	(0.0213)	(0.0250)	(0.0355)	(0.0162)	(0.0149)
Post × High Labor Market Exposure	-0.1444**	-0.0091	-0.0454*	-0.1074***	-0.0070	-0.0228*
	(0.0577)	(0.0153)	(0.0255)	(0.0370)	(0.0124)	(0.0137)
Obs	160,000	160,000	96,000	2,210,000	2,210,000	1,350,000

Panel C: Market Share Includes Inventors with Any Patent in a Technology Class.

	Target Inventors			Acquirer Inventors		
	Number of Patents	Log Annual Earnings	Separation Rate	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0245	-0.0069	0.0592**	0.0057	-0.0147	-0.1038***
	(0.0360)	(0.0208)	(0.0238)	(0.0364)	(0.0163)	(0.0150)
Post × High Labor Market Exposure	-0.1320***	-0.0367	-0.0698*	-0.0517*	-0.0414***	-0.0224
	(0.0475)	(0.0246)	(0.0371)	(0.0283)	(0.0109)	(0.0148)
Obs	160,000	160,000	96,000	2,210,000	2,210,000	1,350,000

Panel D: Weighted Average of HHI and Change in HHI across Technology Classes.

	Target Inventors			Acquirer Inventors		
	Number of Patents	Log Annual Earnings	Separation Rate	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0143	-0.0080	0.0601**	0.0038	-0.0157	-0.0980***
	(0.0373)	(0.0211)	(0.0244)	(0.0355)	(0.0161)	(0.0148)
Post × High Labor Market Exposure	-0.1775***	-0.0281	-0.0691***	-0.0410	-0.0346***	-0.0513***
	(0.0547)	(0.0185)	(0.0262)	(0.0322)	(0.0097)	(0.0111)
Obs	160,000	160,000	96,000	2,210,000	2,210,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes using alternative measures of labor market concentration. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 4, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 2 and 5, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 4 and 6. Columns 1–3 show the estimates for target inventors and columns 4–6 show the estimates for acquirer inventors. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. In Panel A, we use the less granular 3-digit CPC code to measure technology classes. In Panel B, we use a higher cutoff of 1% to define geographical markets so that commuting zone p is in the same labor market as commuting zone c for an inventor only if the probability of inventors in the same technology class moving from c to p exceeds 1%. In Panel C, we count the number of inventors with *any* patent in technology class m when calculating n_{imp} and n_{mp} in equation 1. In Panel D, we calculate the weighted average of HHI and change in HHI across all technology classes for inventors with patents in multiple technology classes. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A21: Effects of M&As on Inventors Using Labor Market Concentration Based on Inventor-Productivity-Weighted Market Shares

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0327	-0.0123	0.0521**
	(0.0370)	(0.0222)	(0.0265)
Post × High Labor Market Exposure	-0.1236*	-0.0078	-0.0477*
	(0.0716)	(0.0186)	(0.0268)
Post × High Synergy	0.1775**	-0.0728**	-0.0218
	(0.0720)	(0.0326)	(0.0503)
Post × High Text Similarity	-0.0794*	0.0024	-0.0822**
	(0.0458)	(0.0291)	(0.0368)
Post × High Industry Concentration	-0.0707	-0.0156	0.0506
	(0.0681)	(0.0247)	(0.0368)
Post × Horizontal	0.0274	-0.0175	-0.0123
	(0.0455)	(0.0245)	(0.0330)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	0.0021	-0.0176	-0.1032***
	(0.0359)	(0.0162)	(0.0147)
Post × High Labor Market Exposure	-0.0688*	-0.0414***	-0.0403**
	(0.0369)	(0.0143)	(0.0164)
Post × High Synergy	0.0395	-0.0458**	0.0658***
	(0.0518)	(0.0184)	(0.0239)
Post × High Text Similarity	0.0427	-0.0094	0.0338**
	(0.0334)	(0.0140)	(0.0153)
Post × High Industry Concentration	-0.1020***	0.0037	-0.0119
	(0.0318)	(0.0128)	(0.0147)
Post × Horizontal	-0.0256	-0.0269*	0.0064
	(0.0354)	(0.0162)	(0.0181)
Obs	160,000	160,000	96,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes, where labor market shares used for calculating labor market concentration are weighted by inventor productivity measured as the number of patents in the last five years. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The independent variables and controls are defined as in Table 4. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A22: Matching Treated Inventors to Counterfactual Inventors in the Same 4-digit Technological Field and a Different Commuting Zone

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.1099	-0.0017	0.0604**
	(0.0700)	(0.0372)	(0.0303)
Post × High Labor Market Exposure	-0.1758*	-0.0600**	-0.0888***
	(0.0900)	(0.0277)	(0.0313)
Post × High Synergy	0.3464***	-0.0553	X
	(0.1120)	(0.0543)	
Post × High Text Similarity	-0.0488	0.0270	-0.0673*
	(0.0815)	(0.0433)	(0.0384)
Post × High Industry Concentration	-0.1583	-0.0727*	0.0470
	(0.1086)	(0.0378)	(0.0413)
Post × Horizontal	-0.0035	-0.0449	-0.0263
	(0.0795)	(0.0365)	(0.0370)
Obs	69,000	69,000	41,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0121	-0.0178	-0.1316***
	(0.0519)	(0.0206)	(0.0231)
Post × High Labor Market Exposure	-0.1326**	-0.0362*	-0.0588***
	(0.0582)	(0.0189)	(0.0199)
Post × High Synergy	-0.0276	-0.0893***	0.0855**
	(0.1053)	(0.0267)	(0.0345)
Post × High Text Similarity	0.0216	-0.0247	0.0472**
	(0.0571)	(0.0222)	(0.0234)
Post × High Industry Concentration	-0.0627	-0.0064	-0.0084
	(0.0525)	(0.0191)	(0.0219)
Post × Horizontal	-0.0753	-0.0053	0.0145
	(0.0566)	(0.0226)	(0.0213)
Obs	866,000	866,000	530,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes where we match treated inventors to counterfactual inventors with the same primary 4-digit technological field and residing in a different commuting zone from the treated inventor. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The independent variables and controls are the same as in Table 4. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively). Cells marked "X" indicate estimates suppressed under Census disclosure rules.

Table A23: Matching Treated Inventors to Counterfactual Inventors Three Years Before the Merger

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0272	-0.0228	-0.0141
	(0.0321)	(0.0161)	(0.0173)
Post × High Labor Market Exposure	-0.1516***	-0.0341*	-0.0528*
	(0.0492)	(0.0177)	(0.0273)
Obs	128,000	128,000	77,500

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0269*	-0.0307***	-0.1011***
	(0.0142)	(0.0059)	(0.0069)
Post × High Labor Market Exposure	-0.0635*	-0.0357***	-0.0386***
	(0.0378)	(0.0132)	(0.0139)
Obs	1,985,000	1,985,000	1,215,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes when we match treated inventors to counterfactual inventors in year -3 (three years before the merger). The sample includes all inventors who are employed by the target or acquirer firm in year -3 (regardless of whether they are employed by the target or acquirer firm in year -1). Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the merger event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A24: Average Effect of M&As on Inventor Outcomes

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0969***	-0.0275*	0.0053
	(0.0282)	(0.0154)	(0.0204)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0362**	-0.0345***	-0.0886***
	(0.0157)	(0.0065)	(0.0074)
Obs	2,210,000	2,210,000	1,353,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the merger. We control for the *Pre* dummy indicating pre-merger periods in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A25: Event Study Estimates of Talent-Consolidating Mergers on Market-Level Patenting and Wages

	Labor Market HHI		Number of Patents by Non-Merging Firms		Log Inventor Earnings at Non-Merging Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Event	0.0113***	0.0182***	-225.4***	-125.8**	-0.0251***	-0.0131*
	(0.0019)	(0.0040)	(20.88)	(59.61)	(0.0032)	(0.0067)
Tech Field×CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech Field×Year FE	No	Yes	No	Yes	No	Yes
CZ×Year FE	No	Yes	No	Yes	No	Yes
Obs	561,000	561,000	561,000	561,000	561,000	561,000

This table reports difference-in-differences estimates of the effect of talent-consolidating mergers, where talent-consolidating mergers are mergers with predicted change in labor market HHI over 100 points. The unit of observation is a labor-market-year. Each labor market corresponds to a commuting-zone-by-4-digit-technological-field cell. The dependent variables are labor market HHI in columns 1 and 2, the number of patents filed by inventors at non-merging firms in columns 3 and 4, and the log average annual earning of inventors at non-merging firms in columns 5 and 6 (non-merging firms are firms not involved in a merger as acquirer or target throughout our sample period). The static treatment effects are estimated using the Sun and Abraham estimator. All specifications include 4-digit tech field×CZ fixed effects. Columns 2, 4, and 6 additionally include 4-digit tech field×Year and CZ×Year fixed effects. Standard errors are clustered at the labor market level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A26: Changes in the Number of Patents Belonging to the Original Employer around M&As

	Target Inventors		Acquirer Inventors	
	(1)	(2)	(3)	(4)
Post	-0.0666**	-0.0488	0.0203	0.0716*
	(0.0302)	(0.0395)	(0.0177)	(0.0404)
Post × High Labor Market Exposure	-0.0897	-0.0800	-0.0288	-0.0462
	(0.0700)	(0.0674)	(0.0410)	(0.0391)
Post × High Synergy		0.1418		0.0013
		(0.0911)		(0.0608)
Post × High Text Similarity		-0.0497		0.0360
		(0.0534)		(0.0379)
Post × High Industry Concentration		-0.0942		-0.1164***
		(0.0713)		(0.0365)
Post × Horizontal		0.0626		-0.0318
		(0.0509)		(0.0410)
Obs	96,000	96,000	1,350,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of patents belonging to the original employer in year -1 based on equation 3. The dependent variable is the difference between the number of patents filed by the treated inventor and belonging to the original employer and the number of patents filed by the matched counterfactual inventor and belonging to the original employer in a given year (if the inventor switches employer between year -1 and a given year, the number of patents belonging to the original employer is set to zero). Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has an above-median predicted impact on labor market concentration for inventors in markets with above-median initial concentration. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High Industry Concentration* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).