Monopolizing Minds:
How M&As Stifle Innovation Through Labor Market Power*

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Abstract

This paper argues that mergers and acquisitions (M&As) reduce inventors' innovation incentives and outputs by increasing firms' labor market power and limiting the rents inventors can capture. We test this mechanism using individual-level longitudinal data from the U.S. Census Bureau. We find that, at both target and acquiring firms, inventors exposed to greater increases in labor market concentration in already concentrated labor markets produce fewer patents, earn lower wages, and exhibit reduced job mobility following mergers. In aggregate, the negative impact of increased labor market power on inventor productivity outweighs the potential benefits from innovation synergies. Overall, our findings highlight the critical role of labor market dynamics and inventor incentives in evaluating the innovation consequences of M&As.

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1 Introduction

Innovative firms are increasingly being acquired by incumbent firms rather than going public through IPOs (Cunningham et al., 2021; Ederer and Pellegrino, 2023), raising policy concerns about the effects of mergers and acquisitions (M&As) on innovation (Federico et al., 2020). Although M&As may reflect efficiency gains or strategic complementarities, a growing share are motivated by the desire to acquire skilled talent.[1] Recent work shows that these talent-driven deals can harm workers by increasing firms' labor market power (Arnold, 2019; Berger et al., 2025). These trends underscore the need to understand how M&As reshape the labor-market environment facing innovative workers and post-merger innovation activities.

In this paper, we study how M&As influence innovation through changes in labor market power over innovative workers. Our mechanism centers on the idea that when a dominant acquirer absorbs a key innovative rival, the labor market for inventors becomes more concentrated, weakening workers' outside options and strengthening the combined firm's bargaining position. We show that this increase in labor market power suppresses inventors' incentives to innovate, both by dampening expected returns to their investment in human capital or effort and by reducing their mobility to employers that might better reward their skills. Consistent with this mechanism, we document that M&As that have a large impact on firms' labor market power lead to declines in inventors' innovation output, indicating that labor market power can act as an important—yet often overlooked—channel through which mergers affect innovation.

To study how M&As affect innovation activities of inventors, we use individual-level, longitudinal data from the U.S. Census Bureau. The data offer two unique advantages. First, we are able to link patent inventors to survey, census, and administrative employee-employer information at the Census Bureau building on the linkages developed in Akcigit and Goldschlag (2023a). Second, the administrative data allow us to examine a comprehensive set of M&As, including acquisitions of smaller private firms that are not subject to antitrust review and not captured by standard databases like 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 in the five years preceding the merger. There are

[1] This is commonly known as "acqui-hiring", see for example: Ouimet and Zarutskie (2020); Tate and Yang (2023); Beaumont et al. (2025).

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.

We analyze the effects of M&As on inventor outcomes by comparing the inventors at target or acquirer firms to counterfactual inventors who have similar characteristics but do not experience any merger event. We then estimate the differences in inventor outcomes between target or acquirer inventors and their respective counterfactual inventors over time using a dynamic difference-in-differences specification.

To test the labor market power channel, 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. The key identifying assumption is that, in the absence of mergers, the difference between high-exposure inventors and their respective counterfactual inventors, and the difference between low-exposure inventors and their respective counterfactual inventors, would have followed similar trends over time.

We measure labor market power using labor market concentration following prior literature (e.g., Arnold, 2019), 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 a geographical region, 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 a merger may significantly increase labor market power for some inventors while having little effect on others within the same firm.

We further examine the role of synergy and product market power by comparing treated inventors in high-synergy (or high-product-market-competition) mergers with those in low-synergy (or low-product-market-competition) mergers. A merger has high potential innovation synergy if the pre-merger innovations of the two merging firms exhibit high complementarity and low substitutability. Mergers have a high impact on product market competition if the industry of the target and acquirer firms operate in the same industry and the industry has high concentration prior to the merger.

We assess three dimensions of inventor outcomes—patents, earnings, and job mobility—for both target and acquirer inventors. To our knowledge, these have never been systematically studied together in empirical work on M&As and innovation, and certainly not in a setting with rich administrative data. These outcomes are important to consider jointly because they provide a holistic picture of the impact of M&As on innovation and inventors and enable us to test the different channels.

Consistent with the labor market power channel, we find that the negative effect of mergers on inventor productivity is concentrated in cases where mergers substantially increase labor market concentration. 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 exhibit similar trends before the merger, and the gap 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 also see that high-synergy mergers are associated with an increase in inventor productivity, especially at target firms. However, mergers between product market rivals are not associated with a decline in inventor productivity.

High-exposure inventors also have lower earnings and are less likely to move to other firms following the merger, consistent with them receiving lower rents from their innovations and having fewer outside options. Five years after the merger, high-exposure inventors experience 10% lower earnings and 5% lower separation rates at target firms, and 7% lower earnings and 12% lower separation rates at acquirer firms. In contrast, low-exposure inventors see a 4% decline in earnings and a 5% increase in separation rates at target firms, and a 2% drop in earnings alongside a 9% decline in separation rates at acquirer firms (the higher separation rate for low-exposure target inventors may be due to a poor fit with the acquiring firm).

We decompose the effect on patenting and earnings into three components—the effect on job stayers, the effect on job movers, and the effect resulting from changes in separation rates. We find that stayers contribute to the majority of the decline in patenting and earnings (i.e., high-exposure inventors staying at the merged firm produce fewer patents and earn less than the counterfactual inventors staying at their original employer), whereas movers explain the rest of the decline. The results from the decomposition support our interpretation that high-exposure inventors staying at the merged firm have lower incentives to innovate.

We perform several additional tests to address the concern that unobserved shocks affecting high-exposure inventors at target and acquirer firms may coincide with M&As.[2] First, we control for unobserved firm-level shocks by including firm fixed effects or firm-by-commuting-zone fixed effects and show that the results are robust when comparing high-exposure inventors within firms and within firm-commuting-zone cells. Second, to control for unobserved field-specific shocks that are correlated with the concentration of innovation in a field, we construct an analogous measure of the merger's impact on concentration in the innovation field based on the number of patents. We find that accounting for the merger's impact on concentration in the innovation field does not alter the effect of labor market concentration for inventors. We also find similar results when comparing inventors within the same technological field. Third, we run a placebo test using failed mergers and do not see a similar effect on high-exposure inventors. We also show that spinoffs—which reduce firms' labor market power and enhance inventors' incentives to innovate—have the opposite effect on high-exposure inventors compared to mergers (although the effects are not statistically significant due to the smaller sample size).

While the labor market channel makes inventors worse off, the impact on firm profits is ambiguous. On the one hand, firms benefit from increased labor market power, which allows them to extract more rents from successful innovations and recoup more innovation output from the inventors due to lower separation rates. On the other hand, lower inventor productivity reduce total rents and firm profits. Overall, we find that the impact on labor market concentration is not associated with post-merger changes in firm-level labor productivity or earnings per worker. Using the sample of publicly listed firms, we show that high-labor-market-impact mergers do not differ

[2] Note that any shock affecting both high-exposure and low-exposure inventors would not explain our results since we focus on the difference between high-exposure and low-exposure inventors. In addition, any shock affecting only inventors at target or acquirer firms can't explain our results given that we find symmetrical effects across target and acquirer inventors for most of the outcomes.

in terms of merger premiums or short-term returns following the merger announcement, but have significantly lower returns months after the merger. In contrast, high-synergy mergers have higher premiums but do not have higher post-merger returns, suggesting that most of the surplus from innovation synergy are captured by the target firm owners since acquirer firms tend to overbid.

We show that the labor market channel is quantitatively important for the aggregate impact of M&As on innovation. In aggregate, mergers have a negative and significant effect on the number of patents and earnings of inventors at both target and acquirer firms. Although both labor and product market power predict post-merger declines in productivity and earnings, our evidence indicates that labor market power is the dominant channel. Mergers that substantially increase labor market concentration exhibit the largest declines in innovation, but mergers between product market rivals do not lead to larger declines in innovation. Moreover, inventors capture a smaller share of innovation surplus and face higher separation rates following mergers, consistent with labor market power but contrary to product market power predictions.

This paper makes two main contributions: first, we demonstrate that mergers lower inventors' productivity by weakening competition in the labor market; second, we provide systematic evidence that labor market power is a key mechanism driving the negative impact of mergers on innovation. While antitrust authorities have expressed concerns about the potential negative effects of mergers on innovation (Federico et al., 2020),[3] previous work mostly focuses on firm-level investment in innovation and firms' incentives to innovate. This neglects the key role inventors play in driving innovation: for example, Bhaskarabhatla et al. (2021) finds that inventor fixed effects explain the largest part of variation in patenting, and labor costs account for over two thirds of R&D expenditure by US firms.[4] Our empirical evidence highlights the importance of considering labor market power and its impact on inventor incentives in the context of mergers and innovation.

We contribute to several branches of literature. Our paper is most closely related to the literature on how M&As affect innovation. Prior work has documented innovation synergies (Bena and Li, 2014; Li and Wang, 2023), outsourcing of R&D to target firms (Higgins and Rodriguez, 2006; Phillips and Zhdanov, 2013), and how mergers address hold-up problems in innovation investment

[3]For example, section 6.4 of the U.S. Horizontal Merger Guidelines states that "competition often spurs firms to innovate" and that U.S. competition authorities "may consider whether a merger is likely to diminish innovation competition by encouraging the merged firm to curtail its innovative efforts below the level that would prevail in the absence of the merger."

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

(Bena et al., 2023). Several papers show that mergers have anti-competitive effects on innovation and reduce firms' incentives to invest in R&D (Ornaghi, 2009; Szücs, 2014; Federico et al., 2017; Cabral, 2018; Haucap et al., 2019). In a more extreme case, Cunningham et al. (2021) document that pharmaceutical firms engage in "killer" acquisitions to eliminate future competition. Our paper focuses on the supply side of innovation and provides empirical support for Fulghieri and Sevilir (2011)'s key insight that mergers reduce inventor incentives by lowering labor market competition. Our results are also in line with Seru (2014), who shows that target inventors have lower patenting productivity after M&As. In addition, our administrative data enable us to examine the effects of all mergers between innovative firms in the U.S. and expand beyond the typical focus on publicly listed firms.

Our paper also contributes to the literature on the effects of M&As on labor. A large literature has documented negative impacts of M&As on workers' earnings (e.g., Shleifer and Summers, 1987; Lagaras, 2019; He and le Maire, 2022; Arnold et al., 2023). Specifically, Arnold (2019) and Prager and Schmitt (2021) show that M&As that increase labor market concentration more lead to lower worker earnings. Bar-Isaac et al. (2025) show that increasing monopsony power can be a major motivation for mergers and such mergers may be socially inefficient. Our results on inventor earnings are consistent with these results.

We also contribute to the growing literature on labor market power. Recent papers have documented strong negative associations between labor market concentration and wages (Azar et al., 2022; Benmelech et al., 2022; Schubert et al., 2024). We show that M&As contribute to rising labor market power over high-skilled workers as documented in Seegmiller (2021). Importantly, the inventor setting allows us to observe individual-level productivity and output and examine how labor market power affects how surplus is split between firms. Our results highlight that labor market power not only depresses workers' wages but also potentially reduces their human capital investment and productivity by lowering the returns to worker investment.

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 (2023b) 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 the outcome of bargaining depends on their relative bargaining power and each party's outside option. Inventors can withdraw their participation from the innovation project before the second phase and transfer their human capital to other firms. In this model, mergers can affect innovation through synergy, labor market power, or product market power. Below, we discuss intuitions and predictions for these non-mutually-exclusive channels.

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.

The innovation synergy lowers inventors' marginal cost of innovation and enables inventors to achieve more successful innovation with the same level of human capital investment. Therefore, inventors invest more in human capital and produce more innovation and have higher wages. The positive effects are stronger if two merging firms have complementary patenting portfolios. The division of surplus between firms and inventors remains unchanged.

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 the degree of labor market competition they face. When two firms merge, inventors in those firms have fewer opportunities outside the firm, which limits their outside options in bargaining and reduces the share of surplus obtained by the inventor. A growing literature, including Arnold (2019) 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 the variety of firms workers can move to, and higher labor market concentration limits workers' outside 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 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.

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 encouraged each firm to invest aggressively in innovation. Before the merger, firms innovate not only to improve their own products but also to capture market share from rivals, creating strong incentives to push the technological frontier. After the merger, however, innovation by one division increasingly cannibalizes the profits of another, reducing the net return of innovation. As a result, the surplus from innovation to be split between firms and inventors decreases, and inventors reduce their human capital investment and innovation expecting to receive lower wages.

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 innovation is largest when mergers occur in highly concentrated product markets between product market rivals, whereas the labor market power channel predicts the largest decline in innovation when the merger parties compete in the labor market for inventors. 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.[5]

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 information 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, stock options, profit distributions, the cash value of meals and lodging, tips, and other gratuities in most states and, in some states, employer contributions to certain deferred compensation plans such as 401(k) 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.[6] The LEHD earnings data are currently available from the 1980s through 2021 (the start date varies across states and ranges from 1985 to

[5] More generally, increased separations and a larger share of surplus captured by inventors are also true for other mechanisms that reduce the marginal value of innovation.

[6] 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.

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.

Inventor Data. To match inventors to workers in the LEHD, we use linkages between inventor records and the Census Bureau's disambiguated and anonymized person identifiers (known as Protected Identification Keys, or PIKs), developed by Akcigit and Goldschlag (2023a).[7]

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.

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, 2019; 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

[7] The match uses inventor name and location, as well as assignee-firm linkages. See Akcigit and Goldschlag (2023a) for details.

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 earnings and patents in year zero may precede the merger.

4 Empirical Strategy

In this section, we describe our empirical strategy. First, we match each inventor in a target or acquirer firm to a "counterfactual" inventor in a firm without any M&A activities. Second, we use our inventor-firm matched data to measure labor market power and synergy from the merger. Finally, we estimate a dynamic difference-in-differences specification comparing the outcomes of treated inventors and control inventors over time to identify the impact of mergers on inventor outcomes.

4.1 Matching to Counterfactual Inventors

We construct the inventor sample as follows. We refer to an inventor-year observation as experiencing a year-t M&A event when (i) the worker has at least one patent within the recent five years; (ii) the worker has positive earnings in year $t-1$, with earnings of at least \$2,000 in all four quarters;[8] 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 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 $t-5$;

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

- 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.[9]

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.[10] 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 M&A events between 2005 and 2017.[11] Figure 1 plots the number of M&As in each year. Table 1 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. For each inventor, we take the field with the most number of patents as the main technology field. We see that the inventors in our sample span across all industries, with the highest concentration in manufacturing and tech sectors ("Information" and "Professional Services"). The technology 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).

[9] We find that using alternative matching criteria (e.g., requiring the treated and control inventors to be in the same technological field, requiring the control inventor to be in a different commuting zone from the treated inventor) yields similar results. These results are available upon request.

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

[11] We restrict to M&As 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.

4.2 Measuring Labor Market Power and Synergy

To test the labor market power channel, we will look at how the effects of mergers on innovation depend on labor market concentration. Recent labor economics literature documents that higher labor market concentration allows firms to impose larger "markdowns" on worker earnings relative to their marginal product (Arnold, 2019; Benmelech et al., 2022; Schubert et al., 2024). The labor market power channel predicts that the decline in innovation following mergers is larger when mergers increase labor market concentration substantially in already concentrated labor markets.

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). Therefore, we use inventors' fields of specialization instead of industry or occupation. This is because even though inventors often move across industries and occupations,[12] most inventors work in teams and prefer to work with other inventors in the same field (Jaravel et al., 2018; Bhaskarabhatla et al., 2021; Baghai et al., 2024). In fact, conditional on moving, almost all inventors (over 95%) move to another firm with at least one inventor working in the same field. Therefore, an inventor's relevant outside options are firms with inventors innovating in the same field.

Given that high-skilled workers like inventors are more mobile than the average worker (Moretti and Wilson, 2017; Amior, 2024), we do not restrict to local labor markets when defining labor markets. Instead, we use a data-driven geography-mobility-adjusted labor market concentration measure akin to the occupation-mobility-adjusted measure in Schubert et al. (2024) to define labor markets geographically based on empirical patterns of inventor mobility across regions.

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

[12] 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).

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.[13] 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%).[14] 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 then calculate the predicted change in HHI due to the merger for inventors in technology class m in commuting zone c as:

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

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 (2019), 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.[15] 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. Since concentration is defined at the inventor level and depends on the inventor's field and location, each firm can have high-exposure and low-exposure inventors simultaneously.

[13] 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. We also consider 3-digit CPC code in Section 5.5.1.

[14] We describe how we measure the commuting zone of each inventor in Appendix B.3. The baseline measure uses cutoff $x = 0$, and we consider alternative measures in Section 5.5.1.

[15] We calculate the median for the sample of target inventors and the sample of acquirer inventors separately.

To test the synergy channel, we measure potential innovation synergies from the merger based on the complementarity between pre-merger patent portfolios of target and acquirer firms. We use two measures to measure innovation complementarity: 1) *Technology Proximity*, which follows Jaffe (1986) and measures the cosine similarity of the two merging firms' innovation activities in the technology space using patent counts in different technology classes, and 2) *Knowledge Base Overlap* from Bena and Li (2014), defined as the number of patents in the common knowledge base, which is the set of patents that have received at least one citation from both the acquirer's patents and the target's patents with award years from $t-5$ to $t-1$. In addition, innovation synergies are lower if the target's innovation and acquirer's innovation are substitutable. We calculate the text similarity between the target and acquirer's pre-merger patent portfolios to measure substitutability. We also consider the effect of substitutability measured by text similarity separately in our analysis. The details of the text analysis are described in Appendix B.1. We define high-synergy inventors as those with above-median complementarity measured by both the technology proximity and the knowledge overlap ratio as well as below-median substitutability measured by the text similarity.

Finally, to test the product market power channel, we consider product market concentration of the acquirer or target's industry, measured by Herfindahl-Hirschman Index (HHI) based on sales at the 4-digit NAICS level in the year before the merger, as well as whether the acquirer and target firms are in the same 4-digit NAICS industry. High-industry-concentration mergers are mergers occurring in an industry with above-median concentration (we split the median for target firms and acquirer firms separately).

4.3 Empirical Specification

We use the sample of treated inventors and counterfactual inventors to estimate the impact of M&As using a difference-in-differences specification. 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.[16] For each matched pair-year observation, we compute the difference in the outcome of interest between the treated inventor and the counterfactual inventor in a given

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

year s, 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 an M&A event (denoted by j) before year s, and $HighSynergy_{ij}$ is an indicator for high-synergy merger. The control variables X_{ijs} include an indicator for pre-merger periods,[17] 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 inventors. According to the labor market power channel, γ should be negative for inventor productivity and earnings. We extend this specification to further test synergy and product market power channels by interacting the post-event dummy with indicators for high-synergy merger, high-industry-concentration merger, and horizontal merger.

We also consider a dynamic event study specification as follows:

$$\begin{aligned}\Delta Y_{ii'js} = \sum_{k \in -5,-4,-3,-2,0,1,2,3,4,5} &(\gamma_k D^k_{ijs} \times HighLaborMarketExposure_{ij} \\ &+ \mu_k D^k_{ijs} \times LowLaborMarketExposure_{ij}) + \epsilon_{ijs},\end{aligned} \tag{4}$$

where D^k_{ijs} is an indicator for inventor i having experienced the M&A event (denoted by j) k years in the past, and $LowLaborMarketExposure_{ij}$ is the complement of $HighLaborMarketExposure_{ij}$. The coefficients of interest, γ_k (and μ_k), 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.

[17]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.

5 Main Results

5.1 Effects on Surplus Captured by Inventors

Before looking at the effects of mergers on inventors' productivity and earnings, 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 in 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:

$$w_{ijs} = \mu g_{ijs} + \beta Post_{ijs} \times g_{ijs} + \gamma Post_{ijs} \times HighLaborMarketExposure_{ij} \times g_{ijs} + X'_{ijs}\beta + \varepsilon_{ijs}, \quad (5)$$

where g_{is} is the total number or value of patents granted to inventor i in firm j at year s. The value of patents are measured using (normalized) citation counts or excess stock market returns from Kogan et al. (2017). We control for all two-way interactions between g_{ijs}, the post-merger dummy, and the high-exposure dummy.

Consistent with the labor market power channel, we find that γ is negative and significant, suggesting that high-exposure inventors capture a smaller share of surplus from their innovations following mergers (these results are currently under disclosure and will be added to the paper soon).

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 2 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. Low-exposure inventors also experience a 0.062 decline in the number of patents per year, which may be explained by the product market power channel or other channels (which we discuss in Section 6.2).

In column 2, we additionally interact the post-merger dummy with whether the merger has high potential innovation synergy, whether the acquirer's patents and target's patents have similar texts, whether the target firm is in a high-concentration industry, and whether the merger is horizontal (i.e., the acquirer and target firms are in the same industry). The impact of labor market concentration remains unchanged with the additional covariates: high-exposure inventors experience a decline in the number of patents per year by 0.132 relative to low-exposure inventors. We also find that mergers with greater innovation synergy are associated with increased patenting. We find more negative effects when mergers occur in a high-concentration industry, consistent with the product market power channel, although the difference is not statistically significant. We also do not see a larger decline in innovation for horizontal mergers, suggesting that the impact of product market power on innovation is limited.

The next two columns of Table 2 look at the effects on acquirer inventors. The findings for acquirer inventors align with those for target inventors. High-exposure inventors experience a decline in the number of patents per year by 0.088 to 0.102 (a 13–15% decline relative to the mean) following M&As compared to low-exposure inventors, whereas low-exposure inventors do not experience a significant decline in productivity. High-synergy inventors at acquirer firms have more patents, but the difference is not statistically significant.

To assess the relative importance of labor market power, synergy, and product market power in influencing inventors' productivity following mergers and understand the interactions between these channels, we split all inventors into eight groups by whether an inventor has high or low exposure to the merger's impact on labor market power, whether the merger has high or low innovation synergy, and whether the acquirer or target firm is in a high-concentration or low-concentration industry. Figure 2 plots the effects of mergers on the number of patents separately for each group. For target inventors in Panel (a), the two groups with negative and significant effects both have a high exposure to labor market power and low innovation synergies. The four groups with high innovation synergies exhibit higher patenting rates following mergers, but none of the positive effects are statistically significant. This suggests that the synergy partially offsets the productivity loss due to increased labor market power, but is not sufficient to have an overall positive impact on patenting even in high-synergy mergers. Panel (b) shows that acquirer inventors also experience the largest declines in the number of patents when mergers have a large impact on labor market concentration.

We next look at the dynamic effects of mergers on inventor productivity using the event study specification in equation 4. Panels (a) and (b) of Figure 3 plot the effects on the number of patents by high-exposure and low-exposure inventors in target and acquirer firms respectively. In both target and acquirer firms, high-exposure and low-exposure inventors follow similar trends prior to the merger. However, their trends diverge after the merger: for high-exposure inventors, there is a large and significant drop in productivity, whereas the drop in productivity is much smaller and statistically insignificant for low-exposure inventors. The gap 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 3 shows the effects of mergers on the number of high-citation and low-citation patents. For high-exposure inventors in target firms, the number of high-citation patents decreases by 0.071 (22% of the mean) and the number of low-citation patents decreases by 0.061 (18% of the mean). For high-exposure inventors in acquirer firms, the number of high-citation patents decreases by 0.074 (22% of the mean) and the number of low-citation patents decreases by 0.061 (8% of the mean). These results indicate that mergers with a large impact on labor market concentration reduce valuable and influential innovation in both target and acquirer firms. We also consider originality and generality (defined in Appendix B.4) as alternative measures of patent quality in Appendix Tables A1 and A2 and find that high-exposure inventors experience larger declines in low-originality and low-generality patents.

5.3 Effects on Earnings and Job Separations

We next explore the effects of M&As on inventors' annual earnings. When mergers increase firms' labor market power, inventor earnings decline for two reasons: inventors invest less and generate lower innovation output, and they capture a smaller share of the surplus from innovation.[18] Table 4

[18]The earnings results also corroborate the results on patents. For example, one limitation of using patents to measure innovation is that they may miss innovations that are not patented (e.g., scientific publications, trade secrets, or commercialization of innovation). Observing inventors' earnings helps address this concern because a

presents the results with inventors' log annual earnings as the outcome variable. 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.[19]

Panels (c) and (d) of Figure 3 plot the earnings of high-exposure and low-exposure inventors relative to counterfactual inventors over time. There is a temporary jump in the earnings of target inventors in the first year following mergers, which is due to target inventors realizing gains from their equity holdings.[20] In both target and acquirer firms, high-exposure inventors suffer much larger earnings losses than low-exposure inventors. For example, in target firms, high-exposure inventors have 9.6% lower earnings five years after the merger, compared to 3.5% lower earnings for low-exposure inventors; in acquirer firms, high-exposure inventors have 6.7% lower earnings five years after the merger, compared to 1.8% lower earnings for low-exposure inventors.

One limitation of the earnings measure in the Census LEHD data is that we do not observe incentive pay directly. While most of the incentive pay is part of the total earnings, these earnings miss some long-term equity incentives (for example, stock options are included when they are exercised). Since we observe inventors for five years after the merger, and both the earnings losses and productivity declines grow over time, it is unlikely that the lower earnings of high-exposure inventors are compensated by higher long-term equity incentives later on. We also show later that the effects are similar for private firms, where equity incentives are less important.

Table 5 looks at the effects on separation rates of inventors. The labor market power channel predicts lower separation rates due to more limited outside options. We define the separation rate as whether the inventor is no longer employed by the dominant employer in year -1.[21] 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

higher level of non-patented innovations should be correlated with higher earnings.

[19]The table also shows that high-synergy inventors have lower earnings following mergers despite having higher productivity. This is likely because most of the surplus from higher innovation synergy is captured by the shareholders of target firms, which we document later.

[20]In untabulated analysis, we find that the increase in the first year is concentrated in target inventors whose firms are publicly listed prior to being acquired.

[21]For target inventors, the separation rate is one after the merger if the inventor is employed at a firm other than the acquirer firm.

and acquirer firms, respectively, reflecting a greater reduction in outside options for high-exposure inventors. Panels (e) and (f) of Figure 3 show that high-exposure inventors have lower separation rates following mergers in both target and acquirer firms. In target firms, low-exposure inventors are more likely to leave the firm than counterfactual inventors following mergers. This may be due to a poor fit (e.g., culture clash) between the target inventors and the acquirer firm (Kim, 2024),[22] but this effect is dominated by the negative effect of labor market power for high-exposure inventors.

The lower separation rates imply that an additional benefit of higher labor market power for merging firms is that it allows them to retain more inventors and recoup more innovation output from their inventors. To test this directly, we look at the number of patents belonging to inventors staying at the firm. Table 6 shows that the decrease in the number of patents by high-exposure inventors belonging to the merged firm is much smaller than the decrease in the total number of patents by high-exposure inventors and is statistically insignificant. Specifically, the effects on the number of patents are 40% smaller for target inventors (column 2) and 55% smaller for acquirer inventors (column 4) than the effects in Table 2. This suggests that higher retention rates help offset the negative effect on firm innovation output due to lower inventor productivity.

5.4 Heterogeneous Effects

If high-exposure inventors have lower productivity following mergers because of higher labor market concentration and worse outside opportunities, we should expect larger effects for workers who have higher job mobility and are more responsive to external labor market opportunities. Appendix Table A3 explores such heterogeneity interacting pre-merger inventor characteristics with the treatment of high exposure to the labor-market-power impact of a merger. In both the target and acquirer firms, we find more negative effects of high exposure for the most productive, highly-paid, and highly-cited inventors. We also find smaller effects for older workers and workers with higher tenure at the acquirer firm, who are likely to have more firm-specific human capital and lower job mobility.

Appendix Table A4 explores heterogeneous effects by ex-ante firm characteristics. For target firm inventors, the effects are generally stronger for older and larger target firms (or younger and

[22]Some 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, 2019).

smaller acquirer firms), in which case the target and acquirer are more comparable and would compete more fiercely for the same talent prior to the merger. We also compare public and private target and acquirer firms. The effects are larger when the target firm is public and smaller when the acquirer is public, but the differences are not statistically significant. This suggests that our findings also apply to the sample of publicly listed firms that has been extensively studied in the previous literature.

We plot the distribution of high-exposure inventors by technological fields in Appendix Figure A3. 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 large negative effects on patenting in the tech sector due to the high concentration of inventors.

5.5 Robustness and Additional Results

In this section, we first show that our results are robust to alternative measures of labor market concentration, and then discuss confounding factors and threats to our empirical strategy.

5.5.1 Alternative Measures of Labor Market Concentration

We consider four alternative measures of labor market concentration in Appendix Table A5. First, we use the coarser 3-digit CPC code to measure technology classes in Panel A. 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. 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. Finally, 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. Across these measures, we find that high-exposure inventors have lower patents, earnings, and separation rates following mergers, with similar magnitudes to the baseline estimates.

5.5.2 Confounding Factors and Threats to Validity

Our empirical strategy compares treated inventors to matched counterfactual inventors, and the identifying assumption is that treated and counterfactual inventors follow parallel trends in patenting, earnings, and separation rates absent the merger. Supporting this assumption, we find no pre-trends in patenting or earnings prior to the merger in the event study analysis. However, it is possible that mergers coincide with other unobserved shocks to the firm, leading to a classic omitted variable bias. Since we find differential effects for high-exposure and low-exposure inventors, and most of the effects are symmetrical across target and acquirer firms, any unobserved shocks need to affect high-exposure inventors and not low-exposure inventors at both target and acquirer firms to explain our results.[23] Below, we discuss some additional tests to alleviate this concern.

Within-Firm Variation. One possibility is that high-exposure inventors and low-exposure inventors are employed by different firms, and firms that engage in mergers leading to higher labor market concentration may face deteriorating innovation opportunities or want to cut down on their innovation efforts. Since the impact on labor market concentration is defined at the inventor level, we can compare high-exposure and low-exposure inventors within the same firm to control for any firm-level unobserved shocks. Table 7 presents the results adding firm fixed effects to the baseline specification in Table 2. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. Column 1 shows that even comparing within the same firm, high-exposure inventors file 0.104 fewer patents per year at target firms and 0.099 fewer patents per year at acquirer firms. Column 2 further adds firm-by-commuting zone fixed effects and compares inventors with different labor market concentration impact within the same firm and the same commuting zone. The estimates remain similar, although it becomes insignificant for target firm inventors. We find similar effects on earnings and separation rates in columns 4 to 6, although the effects are generally weaker for target firm inventors because target firms are smaller and have less variation within firm-commuting zone cells. These results indicate that any unobserved firm-level or regional-level shocks are unlikely to explain our results.

[23] For example, potential explanations could be that there is more outsourcing of innovation from acquirer to target for high-exposure inventors (Higgins and Rodriguez, 2006) or that high-exposure inventors are more affected by changes in the firm's organizational structure (Seru, 2014), but those would predict asymmetrical effects for target and acquirer inventors.

Field-Specific Shocks. A related concern is that high-exposure inventors may be in technology fields with unobserved negative shocks to productivity. For example, firms may wish to consolidate their R&D efforts through mergers in declining technological fields. The lack of pre-trends mitigates this concern, and we find in unreported analysis that the effects are stronger in technological fields with rising innovations rather than fields with declining innovations. We also find similar results when splitting inventors into high-exposure and low-exposure inventors within technological fields and when we match treated inventors to counterfactual inventors in the same field.

To further address this concern, we construct a measure of the merger's impact on concentration in the innovation field analogous to the measure of impact on labor market concentration for inventors. In particular, we calculate each firm's market share using the number of patents in each technology class rather than the number of inventors, and we use national market shares without restricting to any geographical markets. The merger has a high impact on innovation concentration for an inventor if the inventor's field has an above-median initial innovation market HHI and an above-median predicted increase in innovation market HHI. If firms that are consolidating innovation in a field also face negative shocks around the time of the merger, we should see that inventors experiencing mergers with a high impact on innovation concentration exhibit larger declines in patenting.

Table 8 shows that impact on concentration in the innovation field is not significantly associated with larger declines in patenting or earnings following mergers. In addition, controlling for impact on innovation concentration has little impact on the effect of impact on inventors' labor market concentration. These findings reinforce that our results are unlikely to be explained by high-exposure inventors being in fields with declining productivity and consolidation between firms at the same time. Furthermore, these results suggest that our documented effects are specific to increasing labor market concentration for inventors and not merely driven by higher concentration in the innovation field.

Failed Mergers. To further rule out confounding factors, we conduct a placebo exercise using failed mergers, which are merger deals that were announced but not completed. Firms involved in failed mergers share many characteristics with those in completed mergers, such as motivations for engaging in mergers and innovation dynamics, making them a useful quasi-control group, representing what would have happened in the absence of a completed merger (Seru, 2014). We identify the failed mergers as those listed with a "Pending" status in the SDC Platinum Database. We then match the target and acquirer firms of failed mergers to the Census datasets using firm name and address. The details of the matching procedures are described in Appendix B.2.

Table 9 shows the effects of failed mergers using the same specification as Table 2. We find no statistically significant difference between high-exposure and low-exposure inventors for any of the inventor outcomes at target or acquirer firms. The effects are close to zero and, in some cases, exhibit signs opposite to those associated with completed mergers. This further alleviates concerns that high-exposure and low-exposure inventors might be expected to follow different trends in firms that choose to merge.

Spinoffs. We also explore the reverse treatment of spinoffs, where one firm splits into two standalone firms. Spinoffs should have a positive effect on the number of patents by high-exposure inventors because spinoffs increase labor market competition for inventors and therefore increase their incentives to innovate (Fulghieri and Sevilir, 2011). We use the LBD data to identify spinoffs. Specifically, if the establishments of a firm with firm identifier A split into two firms with identifiers A and B, where firm identifier B is new, we refer to firm A as the parent firm and firm B as the spun-off firm. We then match each inventor in the parent firm to a counterfactual inventor one year before the spinoff using the same criteria as in Section 4.1. High-exposure inventors are defined as inventors with an above-median initial labor market HHI and a below-median predicted change in HHI (or an above-median absolute value of the predicted change in HHI). We exclude cases where all inventors go into one firm after the spinoff and the predicted change in HHI is zero.

Appendix Table A6 shows that following spinoffs, high-exposure inventors experience increases in patenting compared to low-exposure inventors. For example, low-exposure inventors have 0.042 fewer patents per year, whereas high-exposure inventors have 0.004 more patents per year. For inventors who later joined the spun-off firm, low-exposure inventors have 0.041 *fewer* patents per year, compared to 0.046 *more* patents per year for high-exposure inventors. However, the difference between high-exposure and low-exposure inventors is not significant due to the smaller sample size of inventors involved in spinoffs.[24]

[24] The number of spinoffs is smaller than the number of M&As, and because spinoffs are typically not driven by R&D motivations, most of the inventors typically join one of the firms after the spinoff, and the impact on labor

Matching Three Years Before the Merger. Another threat to the validity of our results is that inventors may anticipate the upcoming merger and leave the target or acquirer firm before the merger occurs. This would bias our results because our analysis focuses on inventors in the merging firms one year before the merger, and inventors who leave the firm more than one year before the merger would be missing from our sample. To address this concern, we re-matched treated inventors to counterfactual inventors *three* years prior to the merger using the same criteria. Since most of the mergers occur within one year of announcement,[25] this analysis should incorporate inventors who leave due to news about the merger. However, this leads to higher measurement errors because some of the "treated" inventors left the firm before the merger occurred and are not directly affected by the merger. Appendix Table A7 shows that all of our results remain similar when looking at the sample of inventors who are employed in the target or acquirer firms three years before the merger, suggesting that the bias due to anticipation is quantitatively small.

5.6 Decomposition Between Job-Movers and Job-Stayers

So far, we have compared the outcomes of inventors who were initially employed by target or acquirer firms with those of counterfactual inventors regardless of whether they stay at the merged firm or not. In this section, we decompose the effects of M&As on patenting and earnings between job-movers and job-stayers to understand whether the effects are driven by movers or stayers.

To decompose the differences in outcomes into job-mover and job-stayer components, we write the mean outcome for the treated inventors as $y_t = y_t^m \delta_t + y_t^s(1 - \delta_t)$. Here, the overall average outcome of treated inventors, y_t, is equal to the average outcome among treated job-movers, y_t^m, times the separation rate of treated inventors, δ_t, plus the average outcome among treated job-stayers, y_t^s, multiplied by the complement of the separation rate. Similarly, we can write the mean outcome for the counterfactual inventors as $y_c = y_c^m \delta_c + y_c^s(1 - \delta_c)$, where y_c^m is the average outcome of counterfactual movers, y_c^s is the average outcome of counterfactual stayers, and δ_c is the separation rate of counterfactual inventors. Using these identities, we can decompose the difference between the average outcome of treated inventors and the average outcome of control inventors,

market concentration is small.

[25] 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.

$y_t - y_c$, using the following equation:

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

Given estimates of $\{y_t^s, y_c^s, y_t^m, y_c^m, \delta_t, \delta_m\}$, equation 6 apportions the observed difference in average outcome between treated and counterfactual inventors into three components: the difference in the average outcome of job-movers scaled by the separation rate; the difference in the average outcome of job-stayers scaled by the complement of the separation rate; and the difference in the separation rate scaled by the difference between the outcomes of the movers and the stayers. We then decompose the dependent variable in equation 4 into the three components for high-exposure and low-exposure inventors respectively.[26]

Figure 4 summarizes the results from the decomposition. For each period, we plot two bars indicating the effects on high-exposure and low-exposure inventors (compared to counterfactual inventors) respectively, and we decompose each bar into the three components in equation 6. Panel A shows that for target inventors, the difference between stayers accounts for almost all of the decline in patenting for high-exposure inventors. Panel B shows that for acquirer inventors, stayers and movers both contribute to high-exposure inventors' larger decline in patenting, with stayers explaining a larger part than movers. On the other hand, the lower separation rate of high-exposure acquirer inventors contributes to higher productivity because stayers tend to patent more than movers (i.e., $(y_t^s - y_t^m)$ in equation 6 is positive). Panel C and Panel D depict similar patterns for earnings.

The results from this decomposition indicate that the decrease in patenting and earnings among high-exposure inventors is primarily attributed to the lower earnings and patenting of high-exposure stayers compared to low-exposure stayers, consistent with lower incentives and investment for inventors staying at the merging firms.[27] While inventors can mitigate some of the negative effects

[26]For each year, we calculate the separation rates δ_t and δ_c as the fraction of treated and counterfactual inventors who are no longer employed by the original firm. We then calculate each component of equation 6 by aggregating the difference between the outcomes of treated and counterfactual inventors separately scaled by respective separation rates. For example, we calculate the difference between the outcome of treated movers scaled by δ_c/δ_t and the outcome of counterfactual movers to get the first component regarding movers. We then use the difference as the dependent variable in equation 4 to estimate the effects attributed to movers.

[27]If the results were driven by job displacement after mergers, then we would expect to see movers and changes in separation rates contributing most to the observed effects.

by moving to other firms, we also see fewer patents and lower earnings for high-exposure movers at acquirer firms. This may be because it's harder for movers to find the best match with fewer outside options, or that the lower human capital accumulation has lasting effects on inventors' productivity.

6 Discussion

In this section, we examine the average effect of mergers on inventor outcomes and discuss alternative mechanisms. We then explore how the labor market power channel affects firm profits and post-merger performance.

6.1 Average Effect of Mergers on Inventors

As we discuss in Section 2, the overall effect of mergers on inventor productivity and earnings is ambiguous and depends on the relative strengths of the various channels. To measure the average effect of M&As, we estimate the following event study specification:

$$\Delta Y_{ii'js} = \sum_{k \in -5,-4,-3,-2,0,1,2,3,4,5} \beta_k D_{ijs}^k + \varepsilon_{ijs}, \tag{7}$$

where D_{ijs}^k is an indicator for inventor i having experienced the M&A event (denoted by j) k years in the past.

Figure 5 plots the coefficients β_k, which describe the average difference in outcomes between treated and matched counterfactual inventors relative to the year before the merger event. In all panels, the pre-trends are flat before the merger event, corroborating the parallel trends assumption. Five years after the merger, target inventors have 0.085 fewer patents per year (a 13% decline relative to the mean) and 5.2% lower earnings, whereas acquirer inventors have 0.080 fewer patents per year (a 12% decline relative to the mean) and 2.4% lower earnings. Appendix Table A8 shows the average effect across all post-merger periods. On average, mergers have a negative and statistically significant effect on the patenting and earnings outcomes of both target and acquirer inventors, as well as on the separation rates of inventors at acquirer firms. The average effect on target inventors' separation rates is near zero due to other channels causing higher separation rates of target inventors (e.g. cultural misfit).

While both the labor market power channel and the product market power channel reduce productivity and earnings following mergers, our evidence suggests that product market power channel is dominated by the labor market power channel. First, mergers that primarily increase labor market concentration—rather than product market concentration—are associated with the largest declines in innovation and inventor earnings. Second, inventors capture a smaller share of the surplus from their innovations and experience higher separation rates following mergers, consistent with the labor market power channel but opposite to the predictions of the product market power channel. Overall, our results suggest that the labor market power channel plays a quantitatively important role in shaping the aggregate negative effects of mergers on innovation.

6.2 Alternative Mechanisms

Below, we discuss a few other alternative mechanisms on how mergers affect inventors' innovation output and earnings.

Defensive Patenting/Consolidation. Firms may file "defensive" patents to protect themselves from litigation or competitive threats, rather than to commercialize new technologies. Mergers reduce the risk of litigation from competitors and may lead to fewer patents. Relatedly, the merged firm may consolidate similar innovations to improve innovation efficiency (Li et al., 2023). Both mechanisms predict a larger decline in low-citation patents, as these patents are more likely to be defensive in nature or to be consolidated with other patents. However, we find a larger decline in high-citation patents, suggesting that mergers also reduce substantive and high-impact innovation done by inventors.

In addition, Table 2 shows that inventors experience a larger decline in patenting when the patents of the two merging firms have high text similarity, which is consistent firms cutting defensive patenting or repetitive innovation. However, controlling for these channels does not affect the estimates for labor market exposure.

Organizational Frictions. Following mergers, organizational frictions can arise as two firms integrate different management and organizational practices. These frictions can disrupt ongoing projects and reduce employee productivity, particularly in innovation-intensive activities that rely on tacit knowledge and cross-team collaboration. Target inventors may also need to shift the direction of their innovation toward innovation pipelines of the acquiring firms (Bena et al., 2023). While organizational frictions can contribute to lower productivity of target firm inventors, they should have a much smaller impact on inventors of acquiring firms. Higher organizational frictions should lead to higher separation rates (Kim, 2024). Furthermore, it is not clear that organizational frictions are greater for high-exposure inventors, who would have more coworkers innovating in the same field following the merger. Therefore, it is unlikely that organizational frictions are the main driver of our results.

Outsourcing. Phillips and Zhdanov (2013) show that small firms engage in more R&D in order to sell out to large firms. The outsourcing of innovation from large firms to small firms can potentially explain the decline in innovation following the merger. However, this channel can only explain the decline in innovation for target firm inventors, but does not explain the equally large decline in innovation for acquirer firm inventors. Our results also suggest that most of the surplus from selling out innovative firms is not captured by inventors, as the temporary increase in earnings in the first year after the merger is offset by the persistent decline in earnings in later years.

Internalization of Knowledge Spillovers. Finally, mergers may internalize positive knowledge spillovers (Bloom et al., 2013) or market expansion externality (Dix and Lensman, 2025). This increases the marginal value of innovation and has the opposite predictions from the product market power channel. Therefore, this channel may offset the product market power channel, which may explain the null effect of product market rivalry in Table 2. However, the overall negative effect of merger on innovation suggests that this channel is dominated by other channels leading to lower innovation.

6.3 Impact on Firms

The labor market power channel predicts that mergers have two opposing effects on firm profits: firms can extract greater surplus from innovation, increasing profits, but lower inventor productivity reduces profitability. Firms would choose to merge if the positive effect from rent extraction is larger than the negative effect from lower productivity. We find evidence supporting both effects—inventors have fewer patents and capture a smaller fraction of the surplus, and both effects are stronger for high-exposure inventors. We also show that the lower separation rates of inventors help offset the decline in inventor productivity. The synergy channel, on the other hand, predicts that firm profits increase following mergers.

We examine the effects of labor market power and synergy on firm profits by looking at merger premiums and returns in Table 10. We match the publicly listed target and acquirer firms to the SDC Platinum data to get merger premiums (defined as the ratio of offer price to target stock price) and acquirer firms' post-merger returns. Column 1 shows that acquirers pay 18% more for target firms with high potential innovation synergies, indicating that synergies are highly valued by the bidder. In contrast, acquirers pay lower prices for mergers with high impact on labor market concentration, but the difference is not statistically significant.[28] Columns 2 to 6 show that post-merger returns are slightly lower for high-synergy mergers throughout the post-merger period, suggesting that acquirer firms overpay for synergies and most of the surplus from innovation synergies is captured by the target's shareholders. In contrast, a larger impact on labor market concentration does not correlate with short-term returns immediately after the merger, but strongly predicts lower returns one to three months after the merger. This implies that the negative effect of high-labor-market-impact mergers on firm innovation is initially underestimated by the acquirer and the market.

More generally, the labor market power channel may also apply to other high-skilled labor beyond inventors and reduce worker incentives and productivity more broadly. Appendix Figure A4 shows that there is no decline in labor productivity for both high-labor-market-impact and low-labor-market-impact mergers. Appendix Figure A5 shows that the declines in earnings of other workers are much smaller than those for inventors, and there is no significant difference between high-labor-market-impact and low-labor-market-impact mergers. These results suggest that our documented effects on incentives and productivity are specific to inventors in our sample of mergers.[29]

[28] Both the positive effect from rent extraction and negative effect from lower inventor productivity are stronger for high-labor-market-impact mergers, so the effect of labor market concentration impact on post-merger firm profits is ambiguous.

[29] This could be due to two reasons. First, inventors are highly specialized workers and tend to be concentrated in a small number of firms, and M&As are likely to have a larger impact on labor market concentration for inventors than other workers. Second, inventors' productivity are sensitive to their financial conditions (Bernstein et al., 2021) and inventors capture substantial rents from their innovation (Toivanen and Väänänen, 2012; Kline et al., 2019), so M&As could have a larger effect on their rents and incentives.

While we focus on inventor incentives, merger may also alter firms' incentives to invest in R&D. We empirically examine how firm investment interacts with the labor market power channel by estimating the event study specification 4 with firm-level R&D investment (scaled by lagged total assets) as the dependent variable. Since information on R&D is only available for public firms, this analysis uses the publicly listed firm sample. We focus on changes in R&D investment of the merged firm after the merger because most of the target firms are private and we do not observe the total R&D investment of the combined firm before the merger. In addition, since R&D investment is measured at the firm level, we can only exploit across-firm variation and not within-firm variation in labor market exposure for this analysis.

Appendix Figure A6 presents the results. We see a larger decline in firm-level R&D investment for high-exposure inventors. Since the majority of R&D investment is wages paid to R&D workers, part of the decline in R&D following mergers can be attributed to lower earnings of high-exposure inventors. However, it is worth noting that the average change in R&D investment following mergers is almost zero, and even for high-labor-market-impact mergers, the decrease in R&D is small (less than 1% of assets) and statistically insignificant. This suggests that the decline in firm investment in R&D is small and unlikely to be the main driver of our results.

7 Conclusion

This paper examines how mergers and acquisitions affect innovation by focusing on their effects on inventors. We demonstrate that M&As enhance firms' labor market power and diminish inventors' incentives to innovate, leading to lower patenting productivity, earnings, and job mobility for inventors in both the target and acquirer firms.

Our results are relevant for policy. They point to a quantitatively important negative effect of mergers on innovation due to higher labor market concentration for inventors. However, this channel has been overlooked by antitrust authorities until recently.[30] Our evidence suggests that

[30] The FTC cites "less pressure to compete for the most talented app developers" as one of the reasons to block the proposed merger between Meta and Within in a complaint in 2022, noting that the talent to create triple-A VR experiences is scarce and highly-concentrated. Previously, antitrust authorities in the US and EU have regularly blocked mergers based on anti-competitive effects on innovation, but the focus has been primarily on the reduced innovation incentives of firms, due to the internalization of business-stealing effects arising from parallel innovation efforts of rival firms (Federico et al., 2020). Naidu et al. (2018) propose considering labor market power for merger reviews but do not address innovation-specific effects.

labor market power with respect to inventors should be an important consideration when evaluating mergers between innovative firms.

More generally, the detrimental effects of labor market power on the incentives and productivity of innovative workers may extend to settings beyond mergers. Many firms use non-compete and anti-poaching agreements as well as long-term equity incentives to restrict mobility of their most talented workers. Recently, some firms have poached top talent from startup firms without mergers to bypass antitrust scrutiny.[31] Understanding the interaction between labor market frictions, firm strategies, and innovation represents a fruitful area for future research.

[31] See examples from Microsoft and Amazon.

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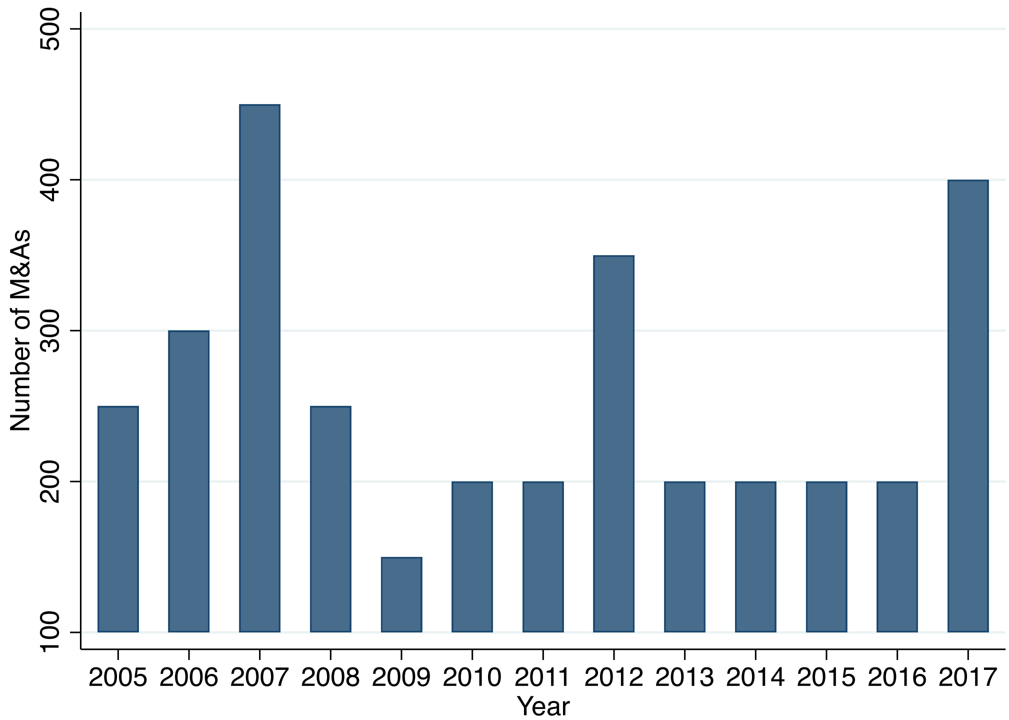
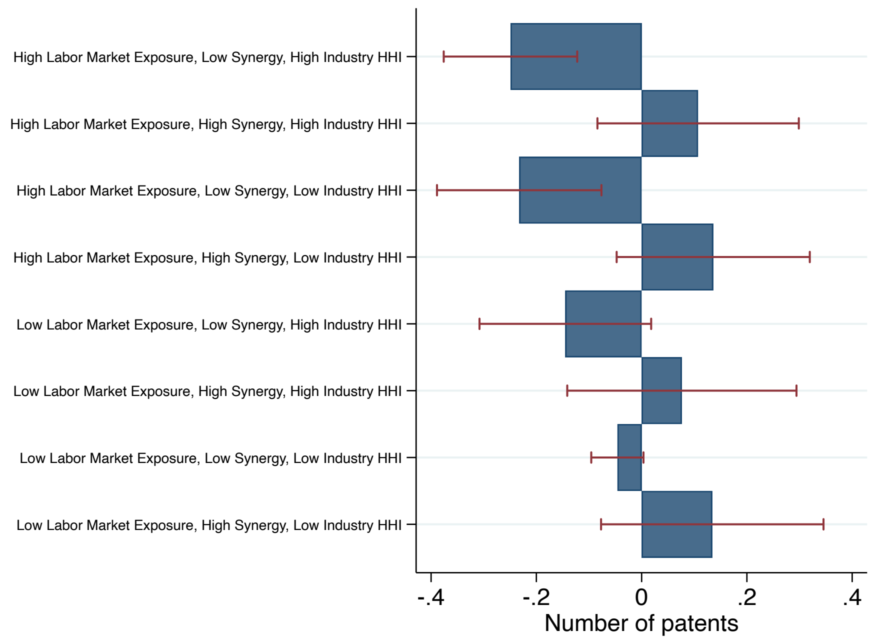
Figure 1: Number of M&As by Year

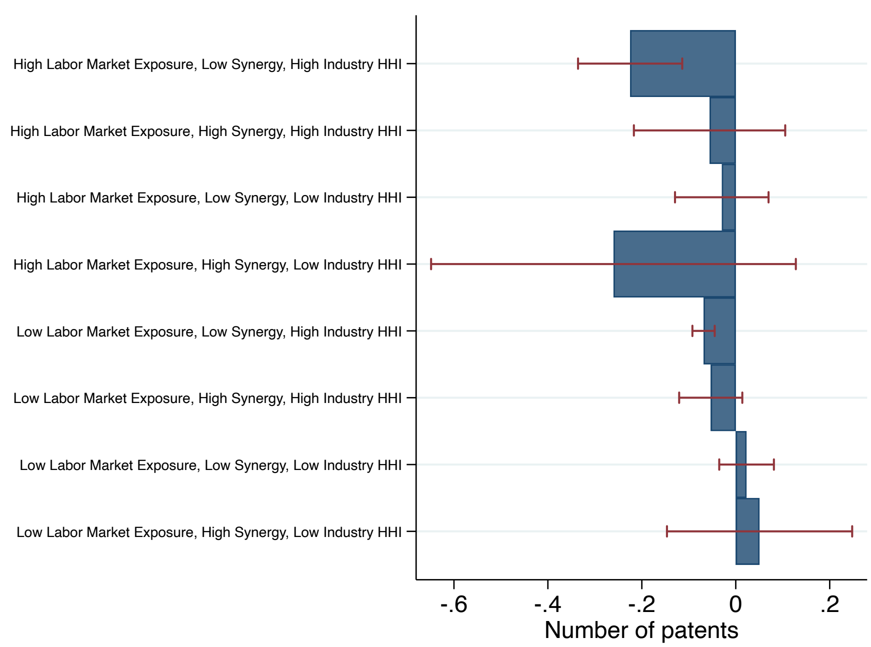


This figure plots the number of M&As in the U.S. each year between 2005 and 2017 in which the target firm has at least one active inventor. We define an inventor as an employee with at least one patent in the five years preceding the merger. The number of observations is rounded in accordance with the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

Figure 2: Changes in the Number of Patents around M&As by Exposure to Labor Market Impact, Synergy, and Industry Concentration



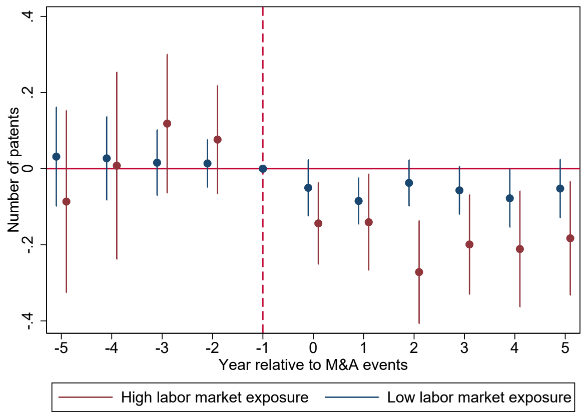
(a) Target Inventors



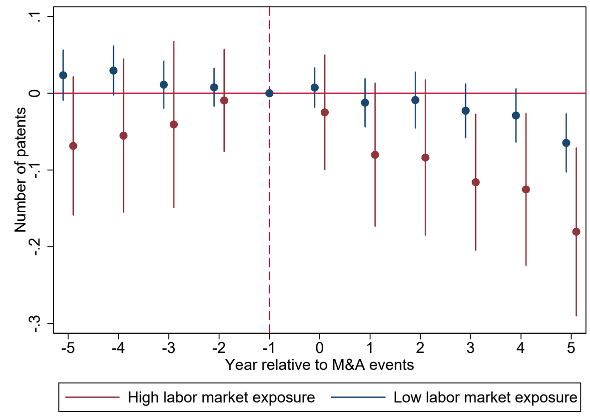
(b) Acquirer Inventors

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.

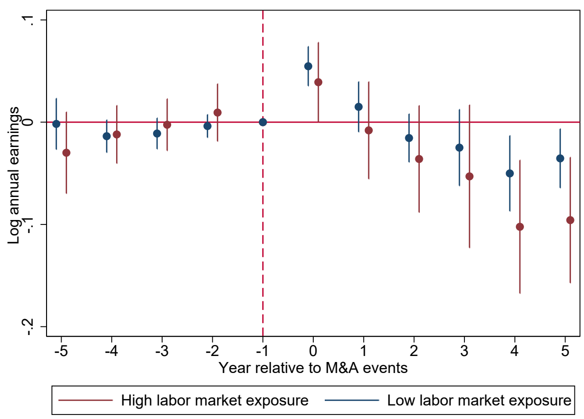
Figure 3: Changes in Inventor Outcomes around M&As for High-Labor-Market-Exposure and Low-Labor-Market-Exposure Inventors



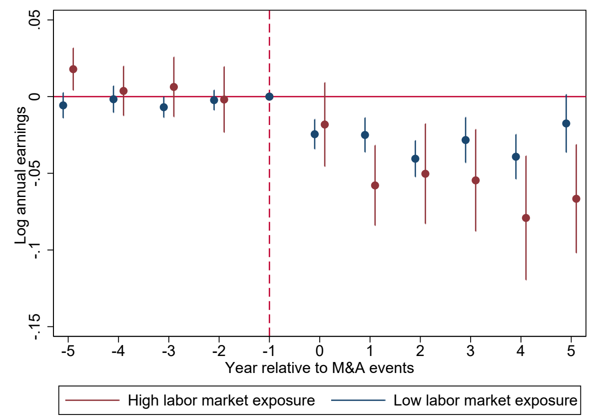
(a) Number of Patents, Target Inventors



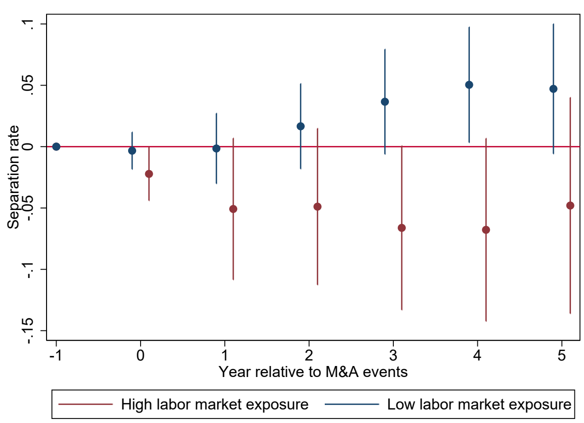
(b) Number of Patents, Acquirer Inventors



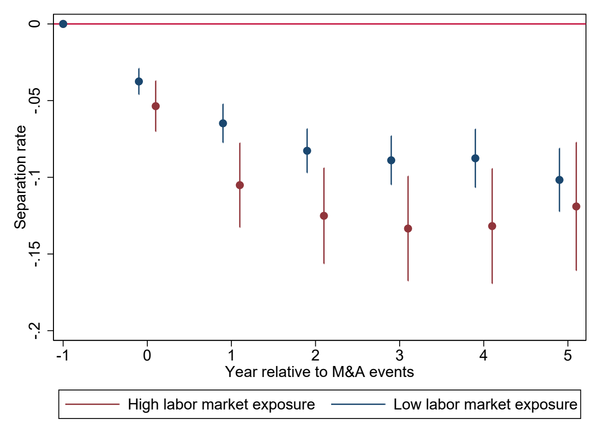
(c) Log Annual Earnings, Target Inventors



(d) Log Annual Earnings, Acquirer Inventors



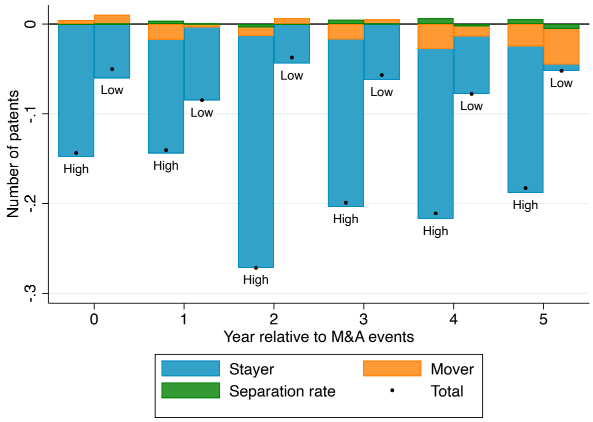
(e) Separation Rate, Target Inventors



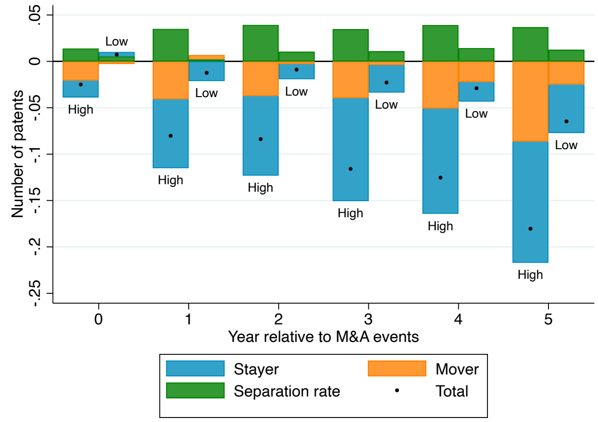
(f) Separation Rate, Acquirer Inventors

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).

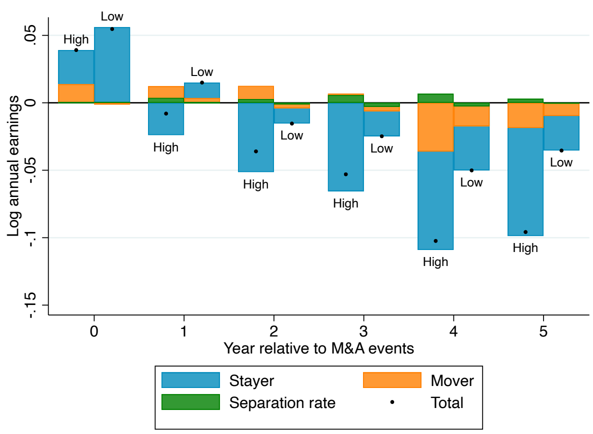
Figure 4: Decomposition of the Changes in Inventor Outcomes around M&As Between Stayers and Movers



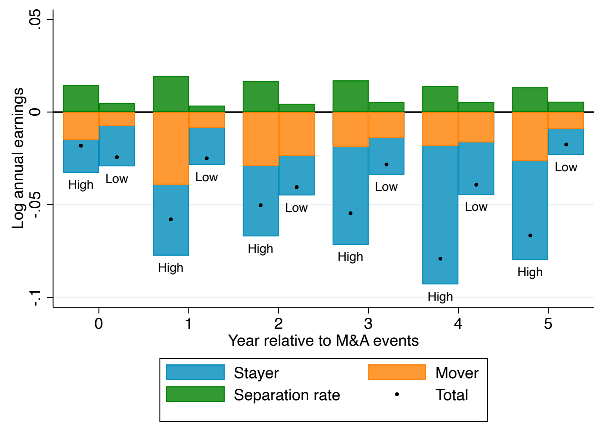
(a) Number of Patents, Target Inventors



(b) Number of Patents, Acquirer Inventors



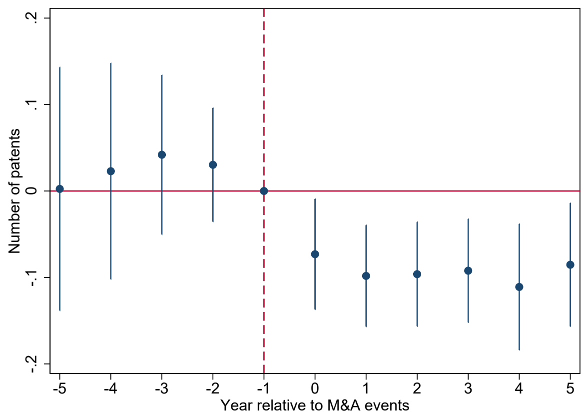
(c) Log Annual Earnings, Target Inventors



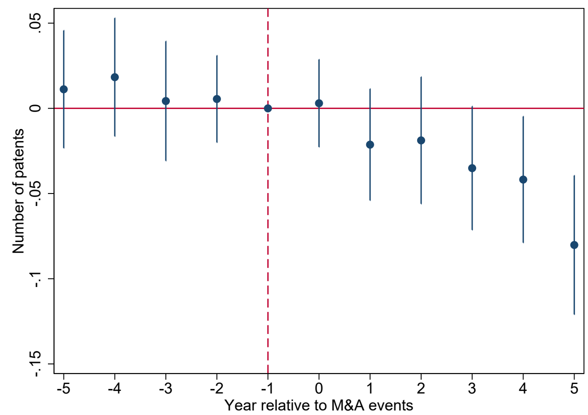
(d) Log Annual Earnings, Acquirer Inventors

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).

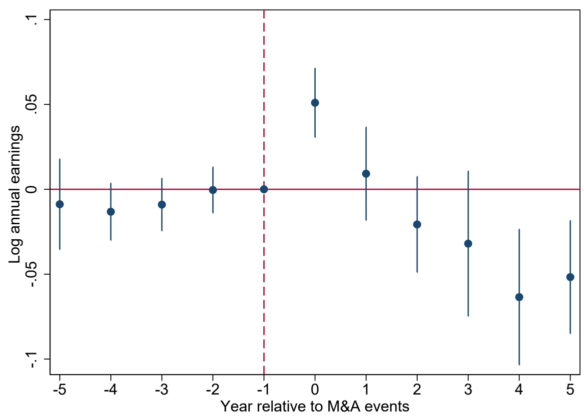
Figure 5: Average Changes in Inventor Outcomes around M&As



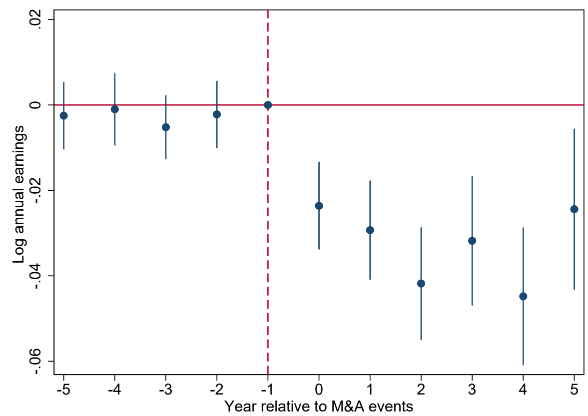
(a) Number of Patents, Target Inventors



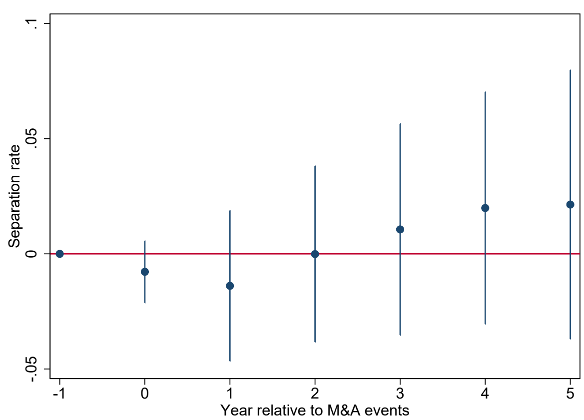
(b) Number of Patents, Acquirer Inventors



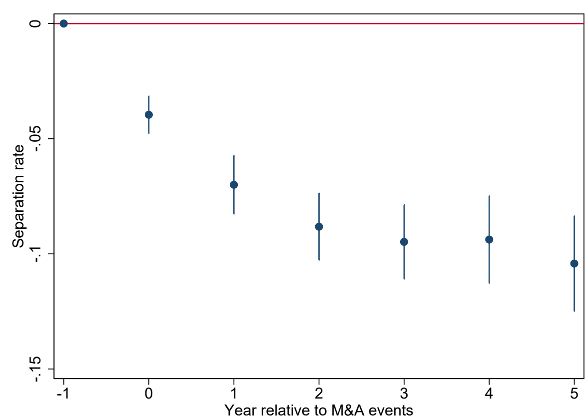
(c) Log Annual Earnings, Target Inventors



(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 average effect of M&As on inventor outcomes based on equation 7. 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).

Table 1: Summary Statistics of 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	0.992
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 2: 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	-0.0245	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 a high predicted impact on the labor market concentration of the inventor. 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 3: 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 a high predicted impact on the labor market concentration of the inventor. 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 4: 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 a high predicted impact on the labor market concentration of the inventor. 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 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 a high predicted impact on the labor market concentration of the inventor. 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 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. 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 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). The *Post* dummy indicates the years after the M&A event. The *High Labor Market Exposure* dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. 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 Inventor Outcomes around M&As Controlling for Firm and Commuting Zone Fixed Effects

Panel A: Target Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0115	0.0426	0.0324	0.0430	0.3806***	0.4389***
	(0.0686)	(0.0764)	(0.0247)	(0.0291)	(0.0692)	(0.0680)
Post × High Labor Market Exposure	-0.1042*	-0.0773	-0.0136	-0.0048	-0.0471*	-0.0198
	(0.0620)	(0.0701)	(0.0162)	(0.0188)	(0.0240)	(0.0222)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm×CZ FE	No	Yes	No	Yes	No	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	0.0275	0.0262	0.0087	0.0090	-0.2004***	-0.2101***
	(0.0357)	(0.0356)	(0.0186)	(0.0185)	(0.0132)	(0.0124)
Post × High Labor Market Exposure	-0.0990***	-0.0928**	-0.0314**	-0.0299**	-0.0345***	-0.0339***
	(0.0363)	(0.0362)	(0.0136)	(0.0137)	(0.0118)	(0.0117)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm×CZ FE	No	Yes	No	Yes	No	Yes
Obs	2,210,000	2,210,000	2,210,000	2,210,000	1,350,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes with firm fixed effects or firm-by-commuting-zone 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 a high predicted impact on the labor market concentration of the inventor. 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. All columns include firm fixed effects (where firm is the dominant employer in year $t-1$), and columns 2, 4, and 6 additionally include firm-by-commuting zone 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 8: Impact on Innovation Concentration and Changes in Inventor Outcomes around M&As

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0195	-0.0051	0.0615***
	(0.0355)	(0.0194)	(0.0238)
Post × High Labor Market Exposure	-0.1304**	-0.0340*	-0.0745***
	(0.0540)	(0.0187)	(0.0237)
Post × High Impact on Innovation Concentration	-0.0046	-0.0101	0.0150
	(0.0557)	(0.0163)	(0.0210)
Post × High Synergy	0.1938**	-0.0618*	-0.0159
	(0.0779)	(0.0348)	(0.0480)
Post × High Text Similarity	-0.0821	0.0083	-0.0843**
	(0.0542)	(0.0282)	(0.0329)
Post × High Industry Concentration	-0.0790	-0.0181	0.0467
	(0.0669)	(0.0244)	(0.0347)
Post × Horizontal	0.0202	-0.0214	-0.0179
	(0.0477)	(0.0235)	(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	0.0139	-0.0172	-0.1011***
	(0.0342)	(0.0155)	(0.0149)
Post × High Labor Market Exposure	-0.1108***	-0.0224*	-0.0469***
	(0.0381)	(0.0122)	(0.0136)
Post × High Impact on Innovation Concentration	0.0363	-0.0448**	0.0388
	(0.0501)	(0.0177)	(0.0275)
Post × High Synergy	0.0300	-0.0405**	0.0586**
	(0.0489)	(0.0183)	(0.0234)
Post × High Text Similarity	0.0365	-0.0046	0.0276*
	(0.0329)	(0.0138)	(0.0146)
Post × High Industry Concentration	-0.1037***	0.0016	-0.0102
	(0.0314)	(0.0127)	(0.0146)
Post × Horizontal	-0.0272	-0.0258	0.0058
	(0.0350)	(0.0160)	(0.0183)
Obs	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 controlling for the impact of M&As on innovation concentration. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The *High Impact on Innovation Concentration* dummy indicates that the merger has a high predicted impact on innovation concentration defined using market shares based on the number of patents within each technology class (see details in Section 4.4). Other variables are defined as in Table 2. We control for the *Pre* dummy indicating pre-merger periods, the *High Labor Market Exposure* dummy, the *High Impact on Innovation Concentration* dummy, the *High Synergy* dummy, the *High Text Similarity* dummy, the *High Industry Concentration* dummy, the *Horizontal* dummy, 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 9: 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 a high predicted impact on the labor market concentration of the inventor. 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 10: Merger Premiums and Post-merger Returns of High-Labor-Market-Impact and High-Synergy M&As

	Merger Premium	1-day Return	1-week Return	4-week Return	60-day Return	90-day Return
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Market Impact	-0.0717	-0.0077	-0.0220	-0.0923***	-0.0852**	-0.1048**
	(0.1083)	(0.0170)	(0.0204)	(0.0355)	(0.0423)	(0.0487)
High Synergy	0.1807*	-0.0316*	-0.0294	-0.0139	-0.0469	-0.0304
	(0.1069)	(0.0182)	(0.0218)	(0.0379)	(0.0450)	(0.0519)
Obs	250	500	500	500	500	500

This table reports OLS estimates of regressing financial outcomes of mergers (merger premiums or post-merger returns) on merger characteristics (labor market impact and synergy). 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 6, the dependent variables are log changes in the acquirer's stock price from 1 day before the merger announcement to 1 day, 1 week, 4 weeks, 60 days, or 90 days after merger announcement. *Labor Market Impact* 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 a high predicted impact on the labor market concentration of the inventor. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. 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 $\kappa : \mathcal{J} \rightarrow \mathcal{K}$ 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.[32] 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

[32] 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.[33] 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

[33] 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.[34] 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.

[34] 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.[35] 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.

[35] 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.

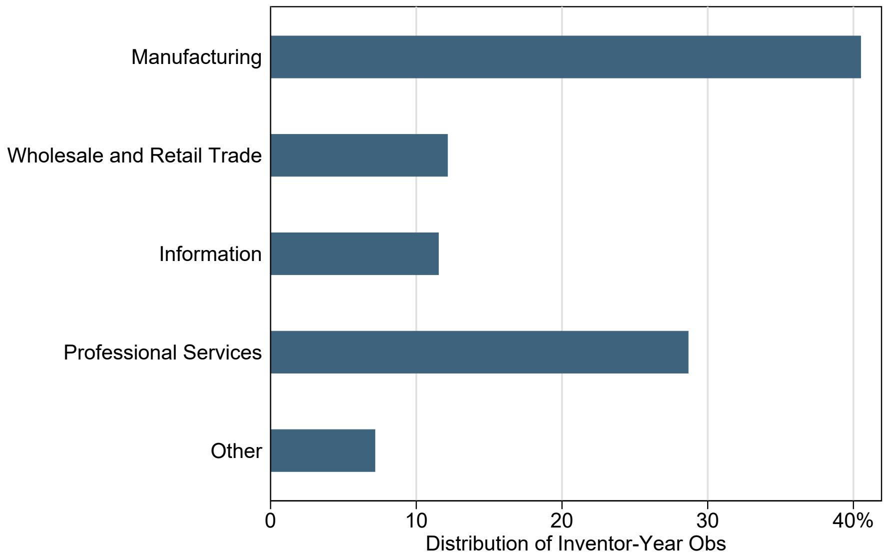
B.4. Patent Quality Measures

Originality. The originality score will be low if a patent cites previous patents in a narrow set of technologies, whereas citing patents in a wide range of fields leads to a high score. Originality for patent i is defined as $1 - \sum_j c_{ij}^2$, where c_{ij} is the percentage of citations that patent i makes that belong to patent class j.

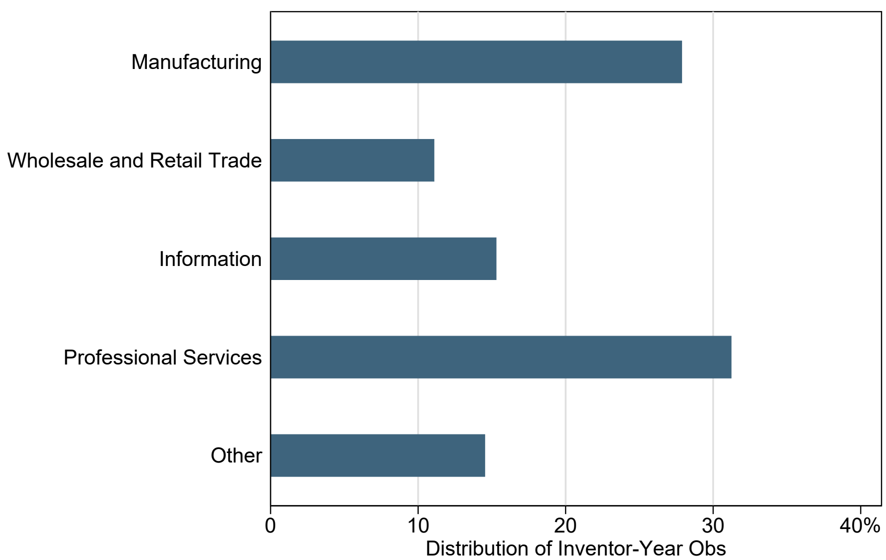
Generality. A high generality score indicates that the patent influenced subsequent innovations in a variety of fields. Generality for patent i is defined as $1 - \sum_j s_{ij}^2$, where s_{ij} is the percentage of citations received by patent i that belong to patent class j. Thus, if a patent is cited by subsequent patents that belong to a wide range of fields the measure will be high, whereas if most citations are concentrated in a few fields it will be low (close to zero).

C. Additional Tables and Figures

Figure A1: Distribution of Inventors by Industry Sector



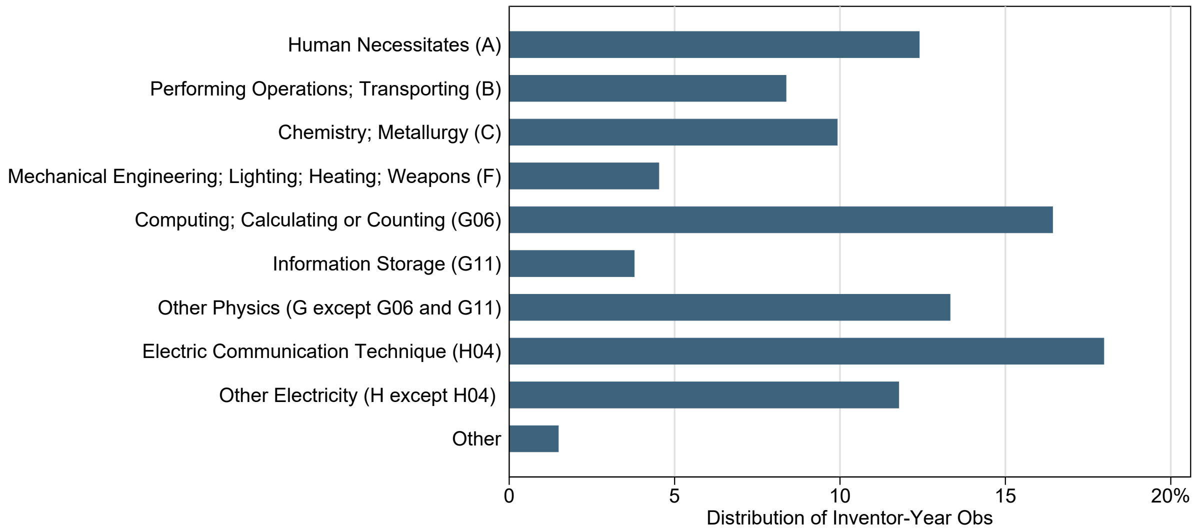
(a) Target Inventors



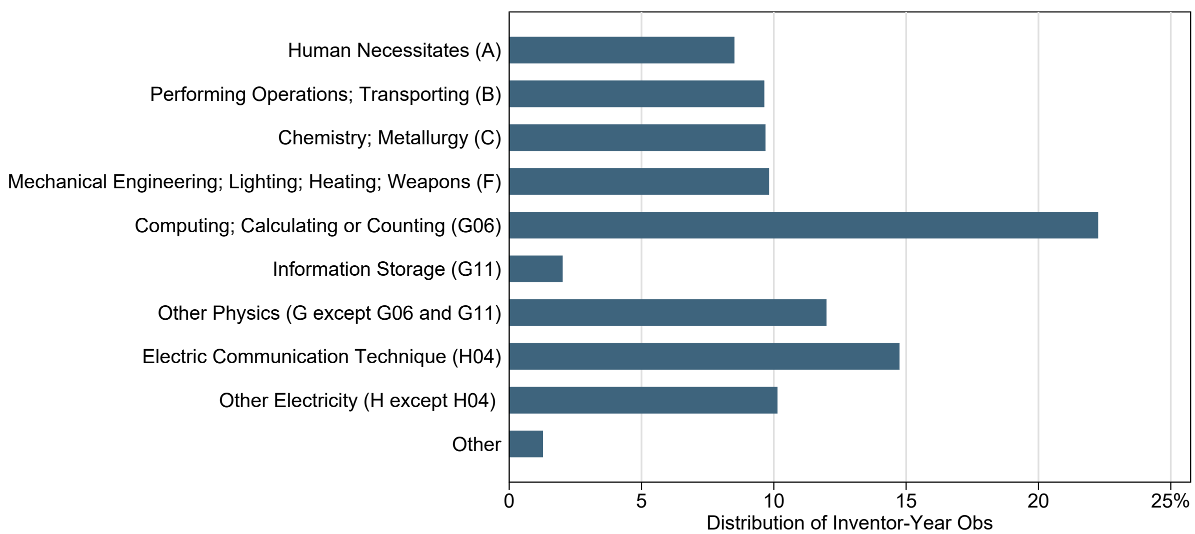
(b) Acquirer Inventors

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



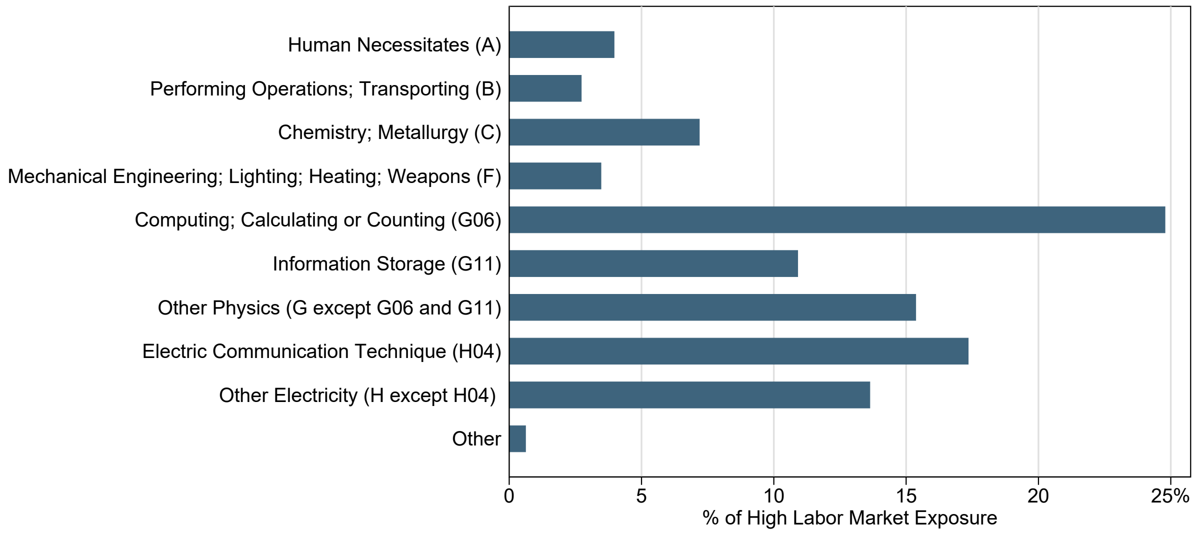
(a) Target Inventors



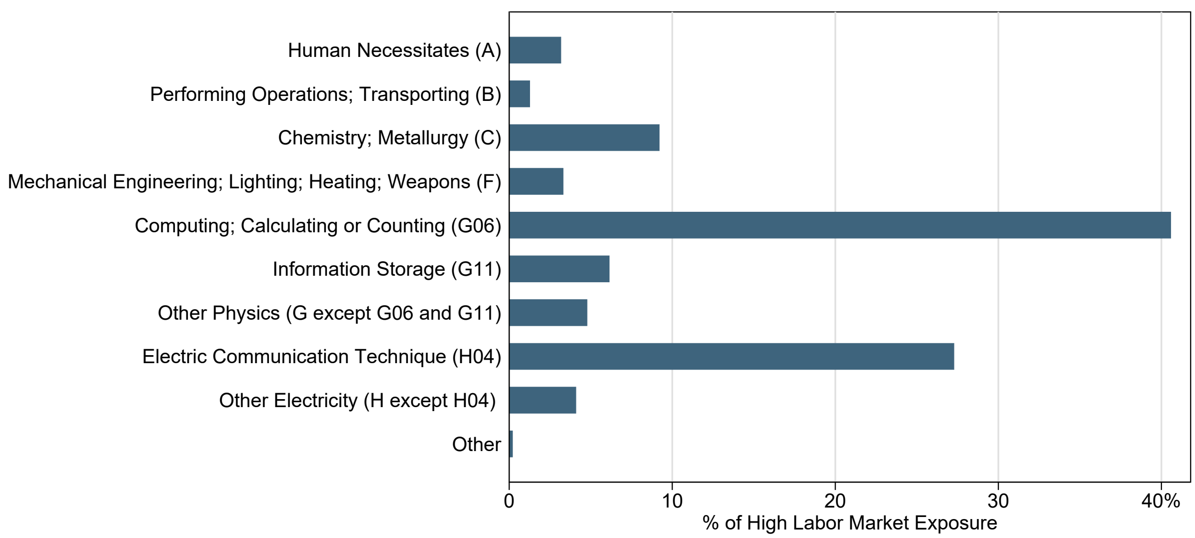
(b) Acquirer Inventors

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



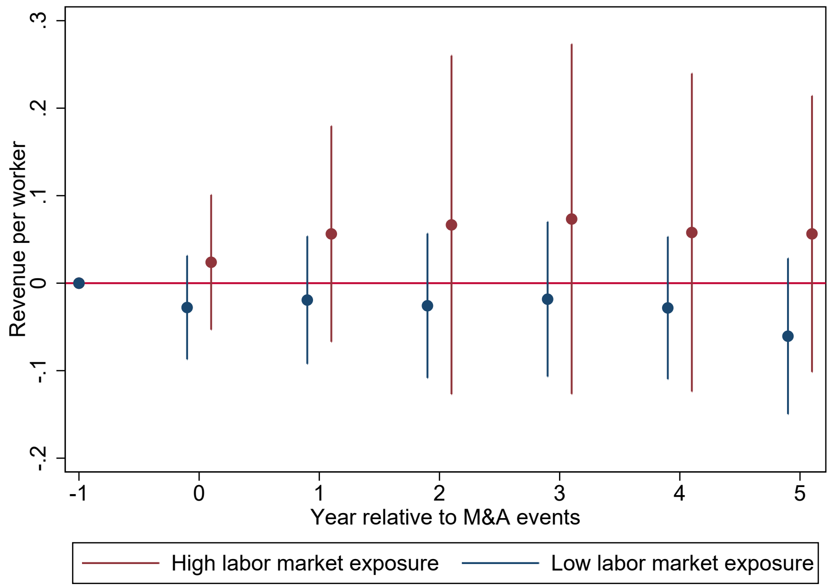
(a) Target Inventors



(b) Acquirer Inventors

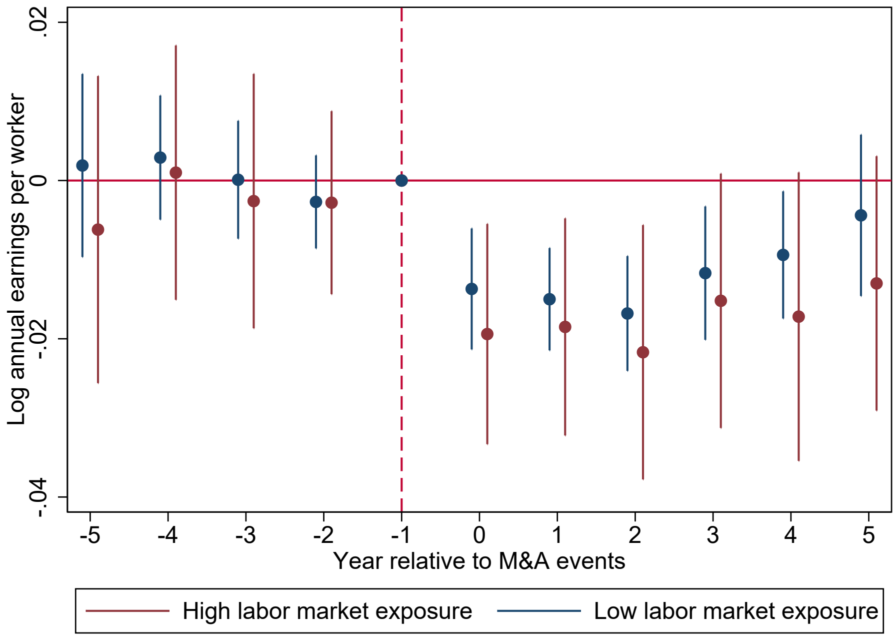
This figure plots the distribution of high-labor-market-exposure inventors (inventors experiencing M&As with a high predicted impact on labor market concentration) in our sample by technological fields. Each inventor is assigned to a primary field based on the area in which they filed the most patents 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 Firm Labor Productivity around M&As

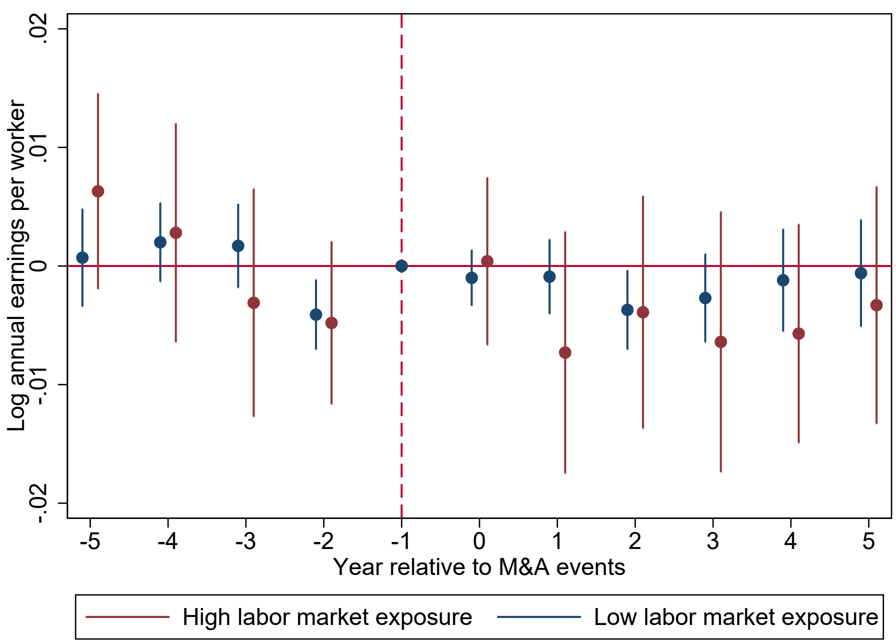


This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on revenue per worker of the merged firm by high-labor-market-exposure and low-labor-market-exposure inventors based on equation 4. The dependent variable is firm-level log revenue per worker of the inventor's employer (firm-level revenue and employment are from the LBD data).

Figure A5: Changes in Firm Average Wage around M&As



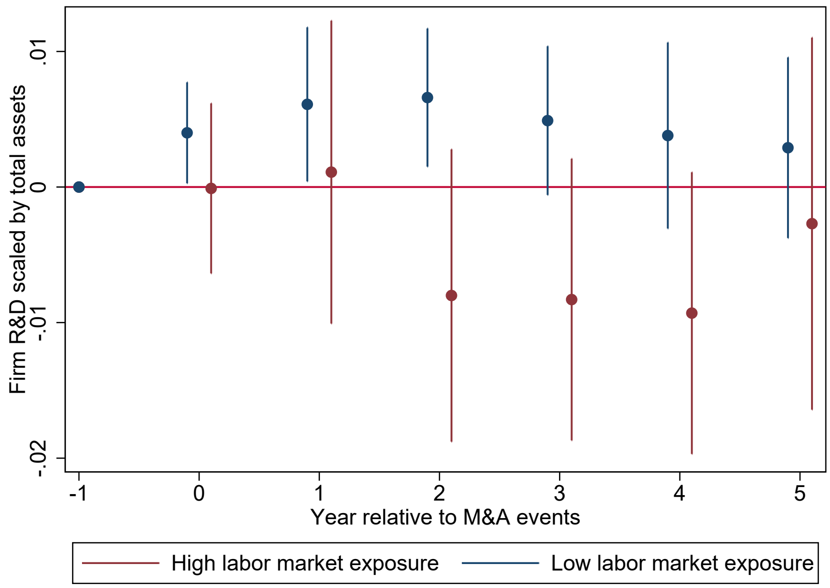
(a) Target Inventors



(b) Acquirer Inventors

This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on firm average wage by high-labor-market-exposure and low-labor-market-exposure inventors based on equation 4. The dependent variable is log earnings per worker (total wage bill divided by employment) of the inventor's establishment.

Figure A6: Changes in Firm R&D around M&As



This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on R&D of the merged firm by high-labor-market-exposure and low-labor-market-exposure inventors based on equation 4. The dependent variable is firm-level R&D expenditure over lagged total assets of the inventor's employer (both R&D and total assets are from the Compustat data).

Table A1: Changes in Patent Quality Measured by Originality around M&As

	Target Inventors		Acquirer Inventors	
	Number of High-Originality Patents	Number of Low-Originality Patents	Number of High-Originality Patents	Number of Low-Originality Patents
	(1)	(2)	(3)	(4)
Post	0.0014	-0.0209	0.0017	0.0118
	(0.0225)	(0.0280)	(0.0169)	(0.0240)
Post × High Labor Market Exposure	-0.0605*	-0.0716	-0.0118	-0.0906***
	(0.0311)	(0.0466)	(0.0175)	(0.0255)
Post × High Synergy	0.1103**	0.0816	0.0130	0.0224
	(0.0547)	(0.0585)	(0.0265)	(0.0310)
Post × High Text Similarity	-0.0314	-0.0517	0.0233	0.0180
	(0.0314)	(0.0354)	(0.0169)	(0.0216)
Post × High Industry Concentration	-0.0307	-0.0481	-0.0492***	-0.0561***
	(0.0369)	(0.0462)	(0.0166)	(0.0195)
Post × Horizontal	-0.0104	0.0304	-0.0004	-0.0261
	(0.0292)	(0.0322)	(0.0200)	(0.0225)
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-originality and low-originality patents based on equation 3. Originality is defined in Appendix B.4. 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 originality filed by the treated inventor and the number of patents with above-median originality 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 originality filed by the treated inventor and the number of patents with below-median originality 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 a high predicted impact on the labor market concentration of the inventor. 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 A2: Changes in Patent Quality Measured by Generality around M&As

	Target Inventors		Acquirer Inventors	
	Number of High-Generality Patents	Number of Low-Generality Patents	Number of High-Generality Patents	Number of Low-Generality Patents
	(1)	(2)	(3)	(4)
Post	-0.0082	-0.0113	-0.0039	0.0174
	(0.0213)	(0.0269)	(0.0211)	(0.0235)
Post × High Labor Market Exposure	-0.0391	-0.0930*	-0.0323*	-0.0701***
	(0.0313)	(0.0485)	(0.0184)	(0.0265)
Post × High Synergy	0.0956**	0.0963*	0.0236	0.0118
	(0.0408)	(0.0518)	(0.0248)	(0.0372)
Post × High Text Similarity	0.0080	-0.0911***	0.0408**	0.0005
	(0.0333)	(0.0335)	(0.0180)	(0.0248)
Post × High Industry Concentration	-0.0881*	0.0093	-0.0443***	-0.0610**
	(0.0459)	(0.0329)	(0.0153)	(0.0248)
Post × Horizontal	0.0315	-0.0116	-0.0029	-0.0236
	(0.0300)	(0.0359)	(0.0193)	(0.0264)
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-generality and low-generality patents based on equation 3. Generality is defined in Appendix B.4. 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 generality filed by the treated inventor and the number of patents with above-median generality 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 generality filed by the treated inventor and the number of patents with below-median generality 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 a high predicted impact on the labor market concentration of the inventor. 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 A3: 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 a high predicted impact on the labor market concentration of the inventor. 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 A4: 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 a high predicted impact on the labor market concentration of the inventor. 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 A5: 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 a high predicted impact on the labor market concentration (using the alternative definitions) of the inventor. 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 A6: 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 a high 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 A7: Effects of M&As on Inventors When 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 a high predicted impact on the labor market concentration of the inventor. 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: 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 based on equation 7. 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).