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) decrease inventors' innovation incentives and outputs by increasing firms' labor market power and reducing the rents received by inventors. We develop a model illustrating this mechanism. Using individual-level longitudinal data from the U.S. Census Bureau, we show that following M&As, inventors in both target and acquiring firms experience declines in patenting productivity and earnings. Consistent with the labor market power channel, the negative effects are more pronounced when mergers significantly reduce labor market competition in an inventor's specific technological field, leading to greater decreases in patents, earnings, and job mobility. Taken together, the findings highlight the importance of considering labor market dynamics and inventor incentives when evaluating the impact of M&As on innovation.

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Introduction

Innovation is a key driver of economic growth and firms' competitive advantage. Innovative firms are increasingly acquired by incumbent firms rather than going to IPOs (Ederer and Pellegrino, 2023), which has spurred policy debates about the impact of mergers and acquisitions (M&As) on innovation (Federico et al., 2020). In this paper, we shed light on this question by studying the impact of M&As on inventors, who are the engine of innovation and an essential input to firm R&D (Bhaskarabhatla et al., 2021; Van Reenen, 2022). We show theoretically and empirically that a key channel through which M&As affect innovation is that M&As enhance firms' labor market power and weaken inventors' incentives to innovate.

We consider a simple theoretical framework with two firms competing in both the product market and the labor market for inventors. The model builds on Fulghieri and Sevilir (2011) and we modify it to incorporate innovation synergies and labor market competition. The firms either operate independently as stand-alone firms or merge into one firm. Inventors exert effort to produce innovation given the firms' organizational structure. After innovations are realized, firms and their inventors engage in ex-post Nash bargaining over the surplus from the innovations. Merging the two firms may bring innovation synergy and increase the value of the innovation. Inventors who have successfully innovated face outside options of either bringing their innovation to the competitor firm or an external market, where their payoff depends on the level of labor market competition in the external labor market.

We show that mergers reduce the level of inventors' effort if the level of product market competition is low and innovation synergy is small. This is because merger reduces labor market competition: under the stand-alone firms, the two firms compete for inventors, and successful inventors get more rents; when two firms merge, inventors expect to get less rents from their innovations and exert less efforts ex-ante. Higher labor market competition in the external labor market enables inventors to have better outside options after the merger and mitigates the negative impact of mergers on inventors' innovation effort. Larger innovation synergies and higher product market competition also mitigate the negative impact of mergers on innovation because synergies increase rents under the merged firm and product market competition erodes rents under the stand-alone structure.

To test these predictions empirically, we use individual-level, longitudinal data from the U.S. Census Bureau to estimate the impact of M&As on inventor outcomes. 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. This builds on the linkages developed in Akcigit and Goldschlag (2023a). The data allow us to unpack the black box of innovative activity and track inventors' employment and earnings outcomes over time.[1] Second, the administrative data allow us to capture a comprehensive set of mergers and acquisitions. In particular, many acquisitions of smaller firms are unreported and not subject to antitrust review (Wollmann, 2019), so we are able to identify smaller merger deals not captured in standard databases on M&As such as the SDC Platinum.

We analyze the effects of M&As on inventor outcomes by comparing the inventors of target and acquirer companies to "counterfactual" inventors who have similar characteristics but do not experience a merger event. Specifically, we match each inventor of the target or acquirer company in the year before the merger to a counterfactual inventor who has the same age, works in the same industry, has similar earnings, employer size, and number of patents, and is not involved in a merger in the five years before or after the event. We then estimate the differences in inventor outcomes between target or acquirer inventors and respective counterfactual inventors over time using a dynamic difference-in-differences specification. The key identification assumption is that inventors in merging firms and matched counterfactual inventors would have had similar trends in terms of employment, earnings, and patenting in the absence of the merger.

Our final sample consists of around 3000 mergers and acquisitions between U.S. innovative firms during the period of 2005–2020. We define an inventor as an employee of the target or acquirer firm who has at least one patent during the 5-year window before the merger event.

[1] Previous studies have used the patent data to identify inventors' employers based on patent assignees, but the method requires the inventor to file patents in a given year.

There are 21,500 unique inventors in the target firms and 109,000 unique inventors in the acquirer firms. An average inventor has 0.7 patents per year.

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 together because they provide a holistic picture of the impact of M&As on the innovation and career trajectories of inventors as well as the innovation and profits of their employers.

We find that M&As reduce the number of patents for inventors in both the target and acquirer firms. Supporting our identification assumption, the number of patents of treated and counterfactual inventors exhibit similar trends before the merger. For both acquirer and target inventors, the number of patents per year declines by about 0.1 after the merger, which is 12–14% of the mean. The negative effect on patenting is persistent over time and is mostly concentrated in low-citation patents.

M&As also have a negative and significant effect on inventors' earnings. Target inventors' earnings see a temporary increase of 5% in the first year after the merger, followed by a decrease by 5% a few years after the merger. Inventors at acquirer firms also experience a 2–5% reduction in earnings in the years following the merger.

Overall, M&As reduce the patenting productivity and earnings of inventors at both target and acquirer firms, consistent with our theoretical mechanism that M&As reduce inventors' incentives to innovate. We also examine whether inventors are more likely to switch firms following M&As. Previous studies document that M&As are associated with increased employee turnovers (Kim, 2024). Surprisingly, we see no change in separation rates for target inventors and a negative and significant effect on separation rates for acquirer inventors. Five years after the merger, acquirer inventors are 10% less likely to move to other firms. The lower job mobility likely reflects two effects of mergers: first, mergers directly reduces inventors' outside options; second, mergers reduce inventors' productivity and make them less attractive to other employers. However, acquirer firms benefit from lower job separations as the number of patents belonging to the acquirer firm increases, even though the productivity of acquirers' inventors is lower.

We decompose the effect on earnings and patents 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 the most to the decline in earnings and patents (i.e., inventors who stay at the merged firm have lower earnings and patenting than counterfactual inventors who stay at their original employer), whereas movers explain the rest of the decline. The difference in separation rates explains none of the effect in the case of target inventors and leads to an increase in patents and earnings in the case of acquirer inventors, because acquirer inventors have lower separation rates and stayers generally have higher earnings and more patents than movers.

Consistent with our model predictions, we find larger negative effects of mergers on innovation when mergers reduce labor market competition by more. Since inventors specialize in narrow technological fields and often work in teams with other inventors in the same fields, we define labor markets for inventors based on their patent classes. An inventor is in a more concentrated market if inventors working in the same technology class are concentrated in a small number of firms. A merger has a high impact on concentration for an inventor when both the target and the acquirer are important players in the field of the focal inventor. Consistent with the labor market competition channel, we find that high-impact inventors in target and acquirer firms suffer larger declines in the number of patents, earnings, and separation rates. Since the concentration measure varies by inventors' fields, we can include firm fixed effects or firm-by-commuting-zone fixed effects to control for firm-specific or firm-location-specific shocks, and find that the results remain robust even when comparing across inventors within the same firm and the same commuting zone.

The impact of mergers also depends on the product market competition and the innovation synergies. We measure product market competition using industry-level HHI, and innovation synergy using the text similarity between the patent portfolios of the target and acquirer firms prior to merger. We find larger effects of mergers when merging firms are in less competitive industries and when the patents of target and acquirer firms are highly similar, which support the predictions from our model.

To address the concern that firms with declining innovation trajectories select into mergers, we repeat our empirical specifications for a sample of failed mergers. We find no statistically significant effect of failed mergers on inventor productivity or earnings, supporting that our results reflect the causal effect of mergers rather than selection.

We employ several additional tests to address potential alternative explanations for lower inventor productivity and earnings following mergers. First, we find almost equal decline in the number of patents by target inventors and by acquirer inventors, implying that outsourcing innovation does not explain our results. Second, we find zero effect on sales per worker or earnings per worker at the target or acquirer firms, which is inconsistent with mergers destroying value at these firms beyond innovation. Third, a potential explanation is that firms focus on more promising innovation projects and terminate less promising ones. Contrary to this explanation, we find a decline in highly-cited patents and a decline in patenting and earnings for highly-cited inventors.

This paper makes two main contributions: first, we provide systematic evidence using detailed individual-level data that mergers have a detrimental effect on innovation; second, we highlight the key role of labor market competition in driving the effect. While antitrust authorities have expressed concerns about potential negative effects of mergers on innovation (Federico et al., 2020),[2] previous work on this topic mostly relies on firm-level innovation measures and focuses on firms' incentives to innovate. This neglects the 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

[2] For example, section 6.4 of the US Horizontal Merger Guidelines says that "competition often spurs firms to innovate" and that US 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."

two thirds of R&D expenditure by firms.[3] Our empirical evidence highlights the importance of considering labor market power and its impact on inventor incentives in the context of merger and innovation.

We contribute to several branches of literature. First, our paper is most closely related to the literature on how mergers affect innovation. Several papers document synergistic gains from mergers (Bena and Li, 2014; Li and Wang, 2023) or the outsourcing of R&D from acquirers to targets (Higgins and Rodriguez, 2006; Phillips and Zhdanov, 2013). Some theoretical papers show that mergers reduce innovation incentives of firms (Cabral, 2018; Federico et al., 2017), which is supported by the lower R&D by merging parties documented in Ornaghi (2009), Szücs (2014), and Haucap et al. (2019). In a more extreme case, Cunningham et al. (2021) document that firms in the pharmaceutical industry engage in "killer" acquisitions to eliminate future competition. Our finding that M&As reduce innovation by inventors is broadly consistent with these studies. While previous studies look at the demand side and firms' incentive to invest in R&D, we focus on the supply side and show that mergers impact the incentives and productivity of innovators. Our results are also consistent Seru (2014), who shows that target inventors have lower patenting productivity after M&As, but we further show that acquirer inventors also have lower productivity and highlight the labor market power channel in explaining the lower productivity of inventors.

Second, we contribute to the literature on the determinants of inventors' productivity and careers. 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 (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; Xue, 2024). Bernstein (2015) and Akcigit and Goldschlag (2023b) show that where inventors work matters

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

for their productivity and earnings: when inventors' employers go public or they move from a young firm to an incumbent firm, their earnings increase and innovative outputs decline. Our evidence show that changes in market structure and labor market competition due to M&As have large and persistent effects on inventors' careers and productivity.

Third, we contribute to the 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). Arnold (2019) and Prager and Schmitt (2021) show that M&As that increase labor market concentration more lead to lower worker earnings. We develop a novel measure of labor market concentration for inventors based on their patent technology classes. M&As are likely to have a stronger effect on labor market power for inventors than the average worker since inventors work in specialized fields and have more highly-concentrated labor markets. Our evidence suggests that stronger labor market power not only lowers earnings but also reduces inventors' ex-ante incentives to innovate and ex-post innovation outputs given that inventors get a lot of rents from their innovations. This resonates with contemporaneous work by Johnson et al. (2023) and Ma et al. (2024) showing that measures to restrict labor mobility and increase labor market power (through non-compete agreements or firm-specific human capital) affect the level and type of innovation outputs.

The remainder of the paper is organized as follows. Section 1 outlines our theoretical framework on how mergers affect labor market competition and inventors' innovation incentives. Section 2 describes our data. Section 3 describes our empirical strategy to estimate the effect of M&As on inventor outcomes. Section 4 presents the main results on the effects of M&As on inventors' patenting productivity, earnings, and employment. Section 5 discusses robustness tests and alternative explanations of our findings. Section 6 concludes.

1 Theoretical Framework

In this section, we propose a simple theoretical model of acquisition and innovation to guide our empirical analysis. Our model builds on Fulghieri and Sevilir (2011), and we extend it by including labor market competition and innovation synergy. All proofs and technical parameter restrictions are in the Appendix.

The model describes two firms operating in imperfectly competitive product and labor markets. Each firm has one inventor, whose innovation creates value for the firms. At $t = 0$, the two firms decide whether to merge or to remain stand-alone firms. At $t = 1$, after observing firms' decision to merge or not, each inventor i chooses effort level e_i, which determines the success probability of the innovation project $p_i(e_i) = e_i \in [0, 1]$. We assume that the effort cost is convex and equals $\frac{1}{2}ke_i^2$, where k is the unit cost of exerting effort. We also assume that the effort is unobservable by the firms, and firms and the inventors cannot write binding contracts contingent on the development of successful innovations. At $t = 2$, firms develop successful innovation projects, and firm and inventors bargain over the surplus.

We first consider the case where two firms operate independently and compete in both the product market and the labor market. The outcome of the bargaining at $t = 2$ depends on whether only one or both inventors generate an innovation. If only one inventor successfully innovates, the innovation will generate payoff $M > 0$ for the firm given that the firm with innovation will be a monopolist in the product market. We assume $M < k$ to ensure that we have interior solutions. Given that the other inventor has failed, the successful inventor can transfer his innovation to the other firm and get payoff δM.[4] As a result, the other firm is willing to offer δM to the successful inventor, and δM represents the inventor's reservation wage. The successful inventor gets the reservation wage plus a portion of the additional surplus $M - \delta M$, which equals $\delta M + \beta(M - \delta M)$, where β is the inventor's bargaining

[4]We can extend our model to have an exogenous probability that the innovation generates a higher value at the other firm, and it will not change any of the conclusions.

power. The firm gets $(1-\beta)(1-\delta)M$.

If both inventors successfully innovate, the two firms compete in the product market and each gets payoff dM. We assume a competition loss of $\Delta = M - 2dM \geq 0$, reflecting that product-market competition erodes profits. Since the two firms compete for inventors (each firm wants to poach the inventor of the other firm and become a monopolist), each inventor gets dM and each firm gets a payoff of zero.

At $t = 1$, inventor i chooses his effort level e_i^S given the effort level of inventor j e_j^S to maximize his expected payoff:

$$\max_{e_i^S} \; w_i^S = e_i^S e_j^S dM + e_i^S(1-e_j^S)(\delta + \beta(1-\delta))M - \frac{k}{2}(e_i^S)^2 \tag{1}$$

Firm i's expected profit π_i^S is $e_i^S(1-e_j^S)(1-\beta)(1-\delta)M$. The Nash equilibrium of the effort subgame for two stand-alone firms is:

$$e^{S*} = \frac{(\delta + \beta(1-\delta))M}{k + (\delta + \beta(1-\delta) - d)M} \tag{2}$$

Next, we consider the case when two firms merge. We show in the Appendix that it is always optimal for the merged firm to retain both inventors instead of firing one inventor. We assume that when an inventor has a successful innovation, he can take it to an external market and get payoff vM. We assume that $v \leq \delta$ and $v \leq d$ so that the external market does not affect payoffs under stand-alone firms. vM represents the inventor's outside option in the labor market (Caldwell and Danieli, 2024), and is lower when labor market concentration is higher (i.e., when similar workers are concentrated in a small number of firms). When only one of the inventors successfully innovates, he gets the outside option vM, plus a proportion of the surplus $M - vM$, which equals $vM + \beta(M - vM)$. The firm gets the remaining surplus $(1-\beta)(1-v)M$.

When both inventors generate successful innovations, the merged firm gets a total payoff of $(1+r)M$ from both innovations, where $r \geq 0$ represents the synergy between the two innovations. The two inventors compete with each other, therefore when $r > v$, each inventor gets the outside option vM plus a proportion of the additional surplus $rM - vM$ equal to $vM + \beta(r - v)M$; when $r \leq v$, each inventor gets the outside option vM. The firm gets $(1 + r)M - 2(v + \beta(r - v))M$ when $r > v$, and $(1 - v)M$ when $r \leq v$.

Inventor i chooses his effort level e_i^M to maximize his expected payoff:

$$\max_{e_i^M} \; w_i^M = e_i^M e_j^M (v + \beta(r - v)^+)M + e_i^M (1 - e_j^M)(v + \beta(1 - v))M - \frac{k}{2}(e_i^M)^2, \tag{3}$$

where $(r - v)^+ = \max(0, r - v)$.

The merged firm's expected profit π^M is $e_i^M e_j^M (1 - v + (1 - 2\beta)(r - v)^+)M + e_i^M (1 - e_j^M)(1 - \beta)(1 - v)M + e_j^M (1 - e_i^M)(1 - \beta)(1 - v)M$.

The Nash equilibrium of the effort subgame after two firms merge is:

$$e^{M*} = \frac{(v + \beta(1 - v))M}{k + \beta(1 - v - (r - v)^+)M} \tag{4}$$

Proposition. The level of inventor effort and inventor's expected payoff is lower under the merger than under stand-alone firms if and only if $d > \max\{d_0, 0\}$, where

$$d_0 = \frac{(v + (r - v)^+ - (1 - \beta)(1 - v))\,(\delta + \beta(1 - \delta)) - (1 - \beta)(\delta - v)k/M}{v + \beta(1 - v)}.$$

In our model, merger may either increase or decrease inventors' innovation efforts for the following reasons. First, following the merger, firms no longer compete for inventors, therefore inventors get lower rents from their innovations and have less incentives to innovate. Second, product market competition erodes firms' profits, and merger eliminates product market competition and potentially increases payoff from innovation when both inventors succeed. Third, mergers may create synergies so that two successful innovations may be more valuable than one successful innovation for a firm, which increases inventors' rents and their incentives to innovate.

Our main empirical tests examine how mergers change the innovation and earnings of inventors. Since the relationship between merger and inventor efforts is theoretically ambiguous, we will test whether mergers increase or reduce inventors' patenting empirically. Furthermore, we will examine how various factors impact the innovation and earnings of inventors following mergers.

While the impact of mergers on inventor effort is uncertain, the following corollary shows that mergers will unambiguously reduce inventor effort when synergy is small and product competition is low.

Corollary 1. A sufficient condition for lower inventor effort and inventor payoff under the merger is $r \leq d$.

The effect of merger on inventors' innovation incentives depends on the level of labor market competition for inventors. We assume that the labor market for inventors is imperfectly competitive ($v \leq \delta$ and $v \leq d$) such that merger between the two firms reduces inventors' labor market competition. In fact, if the labor market for inventors were sufficiently competitive ($v \geq \delta$ and $v \geq d$), merger would have no effect on inventor effort (or even increase inventor effort when synergy is sufficiently high), because the inventors would have the same outside options under stand-alone firms and under the merger. Higher labor market competition raises inventors' outside options under the merger, therefore increasing their incentives and effort to innovate.

The effect of the merger also depends on product market competition and potential synergies. Higher product market competition reduces rents, and therefore reduces inventor effort under the stand-alone firms relative to the merger. Higher synergy increases rents under the merger relative to the stand-alone structure. We formalize these intuitions in the following corollaries, which provide comparative statics with respect to the market-competition and synergy parameters.

Corollary 2. Let β^e denote the effect of the merger on inventor effort: $\beta^e = e^{M*} - e^{S*}$. Merger reduces inventor effort more when the labor market or product market is less competitive, or when the synergy is lower, i.e., $\partial\beta^e/\partial v > 0$, $\partial\beta^e/\partial d < 0$, and $\partial\beta^e/\partial r \geq 0$.

Corollary 3. Let β^w denote the effect of the merger on inventors' expected payoff: $\beta^w = w^{M*} - w^{S*}$. Merger reduces inventors' expected payoff more when the labor market or product market is less competitive, or when the synergy is lower, i.e., $\partial\beta^w/\partial v > 0$, $\partial\beta^w/\partial d < 0$, and $\partial\beta^w/\partial r \geq 0$.

Merger may increase or decrease firms' expected profits. On the one hand, given inventor's effort level, the merged firm earns higher profits than stand-alone firms because it can not only get higher value from the innovation due to lower product market competition and potential synergy, but also extract more rents from inventors with lower labor market competition. Thus firms may benefit from merging even when it reduces the level of inventor effort and innovation. On the other hand, merger may lead to lower inventor effort and reduce the total payoff from innovation. For example, when both employee bargaining power β and outside option v are close to zero, the effort level is close to zero under the merger but positive under stand-alone firms, and merger reduces firms' profits relative to the stand-alone structure. Therefore, from the firm's perspective, it may be optimal to not merge if the ex-ante negative effect on inventor effort dominates the ex-post benefit of market power and synergy.

In this model, we focus on inventors' incentives to innovate and assume that inventor effort is the only input to innovation. In the Appendix, we further consider the case in which firms invest before inventors exert effort. In that case, the merged firm may find it optimal to retain only one inventor, which further decreases inventor effort and payoff.

While our model only has two firms for simplicity, in a more realistic setting with many firms competing in the labor market of inventors, merger can have two effects on inventor mobility across firms. First, merger directly reduces inventor mobility by eliminating inventor movements between the two stand-alone firms. This effect is larger when similar inventors are concentrated in a small number of firms and there are a lot of inventors moving between the two firms before the merger. Second, since inventors who have successful innovations are more likely to be poached by other firms,[5] merger reduces inventor mobility if it reduces inventors' effort and probability of success (and vice versa). This effect is more negative when merger reduces the effort level of inventors by more.

2 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 US 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 US 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 2002). While we include

[5] In our model, after the two firms merge, an inventor moves his innovation to the external market when both inventors successfully innovate and $r < v$.

[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.

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 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 young, privately held firms. Under the Hart-Scott-Rodino (HSR) Act, firms are

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

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

3 Empirical Strategy

In this section, we describe our empirical strategy to estimate the impact of M&As on inventor outcomes. We first match all inventors in target and acquirer firms to "counterfactual" inventors in firms without M&A activities. We then estimate a dynamic difference-in-differences specification comparing the outcomes of treated inventors and control inventors over time.

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 $2000 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 positive earnings in year $t-1$, with no

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

less than \$2000 earnings in all four quarters; and (iv) the observation matches the treated inventor-year observation along five dimensions. Those five dimensions are:

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

Matching on these various dimensions helps in identifying counterfactual inventors that would plausibly exhibit common trends to treated inventors in the absence of M&As. If multiple inventor-t observations satisfy all the criteria, then we pick the inventor-t observation with the closest patent productivity in the recent five years as the counterfactual inventor.

After conducting the matches, we construct a balanced panel of inventor outcomes for each inventor-event i and the matched counterfactual inventor i' for every year between five years before and five years after the merger event.[9] 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. Table 1 reports summary statistics from this sample. As the table shows, treated inventors and counterfactual inventors have similar earnings and number of patents as a result of our matching procedure.

Next, we use the sample of treated inventors and counterfactual inventors to estimate the impacts of M&As using a difference-in-differences specification. In particular, let i denote

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

a treated inventor in a target or acquirer firm and i' denote the matched counterfactual inventor. Let j denote the firm-event combination.[10] 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 year s, denoted as $\Delta Y_{ii's} = Y_{is} - Y_{i's}$. We then regress the difference on event-time indicators in an event-study specification:

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

where D^k_{is} is an indicator for inventor i having experienced the M&A event (denoted by j) k years in the past. The coefficients of interest, β_k, provide the time path of the difference in outcomes between treated and counterfactual inventors relative to the year before the merger event, which is normalized to zero. Note that, because there are no controls, the coefficients β_k represent raw differences-in-differences of the average outcome between treated and counterfactual inventors, comparing other years to year $t-1$. We cluster standard errors at the firm-event level j.

4 Effects of M&As on Inventor Outcomes

This section first presents the effects of M&As on innovation productivity and earnings of inventors in both target and acquirer firms. We then examine the effects on inventor mobility and decompose the effects on productivity and earnings between job-movers and job-stayers. Finally, we empirically test the comparative statics of our model regarding labor market and product market competition.

[10] For a given event, firm refers to the firm identifier in year $t-1$. A firm may have multiple events, and each event involves two or more firms.

4.1 Effects on Patenting, Earnings, and Inventor Mobility

We first examine the effects of M&As on inventors' innovative productivity. Our main measure of inventor productivity is the number of patents applied in a given year that are eventually granted. Figure 1 plots the point estimates and 95% confidence intervals from equation 5 for the number of patents. Panel A plots the effects for target inventors and Panel B plots the effects for acquirer inventors. In both panels, the pre-trends are flat before the merger event, corroborating the common trends assumption underlying the difference-in-differences analysis that in the absence of the merger, patenting productivity of target or acquirer inventors and of counterfactual inventors would have trended similarly. Panel A shows that inventors at target firms experience a decline in patenting which starts immediately after the merger and persists over time. In Table 2, we impose a constant coefficient for all post-treatment periods instead of allowing the effects to be unrestricted over time. The static effect, as shown in column 1 of Panel A in Table 2 is -0.0969 (standard error = 0.0282). Given that the average number of patents per year is 0.67 for target inventors, this represents a 14% decline in the number of patents relative to counterfactual inventors. Panel B shows that M&As also reduce the number of patents for inventors at acquirer firms. The effects grow gradually over time, and by five years after the merger, inventors at acquirer firms have 0.0802 (standard error = 0.0208) fewer patents than counterfactual inventors, which is a 12% decline relative to the mean of 0.68.

To measure the quality of patents, we consider the number of forward citations normalized by patent 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. Figure 2 plots the effects of M&As on the number of high-citation and low-citation patents. For inventors in both target and acquirer firms, the effects on the number of low-citation patents are larger and more negative than the effects on the number of high-citation patents. This suggests that the decline in patenting is mainly concentrated in less influential patents, although there is some decline in high-citation patents as well.

Figure 3 plots the differences in the number of patents between inventors in merging firms and counterfactual inventors over time. Panel A shows that the earnings of inventors at target firms increase immediately in the first year following the merger but decline gradually afterwards.[11] However, the increase in earnings is short-lived: the effect becomes negative from year 2, and five years after the merger, target inventors earn 5.2% less than counterfactual inventors. Column 2 of Panel A in Table 2 shows that the static treatment effect of M&As on the earnings of target inventors is -0.0275 (standard error = 0.0154).

Panel B of Figure 3 plots the effects on the earnings of inventors in acquirer firms. The earnings decline immediately and the effects remain negative and significant for five years following the merger. Column 2 of Panel B in Table 2 shows that the static treatment effect of M&As on the earnings of acquirer inventors is -0.0345 (standard error = 0.0065).

While the impact of M&As on inventor effort and earnings is theoretically ambiguous as shown in Section 1, we find that M&As generally reduce the number of patents and earnings of inventors at both target and acquirer firms. This suggests that in the aggregate, the negative effect on inventor incentives due to less labor market competition and lower rents dominates any positive effect from higher rents in the product market and innovation synergy.

Our model predicts that when M&As reduce inventors' effort, inventor mobility also decreases because of two reasons: M&As eliminate mobility between target and acquirer firms; and inventors with lower productivity are less likely to be poached by other firms. We define the separation rate as whether the inventor is no longer employed by the dominant employer in year -1. For target inventors, the separation rate is one after the merger if the inventor is employed at a firm other than the acquirer firm. Therefore, the separation rate is cumulative and turns on once the inventor leaves the firm and joins another firm. Figure 4 plots the differences in separation rates between treated inventors and counterfactual

[11] 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. Therefore, the temporary jump in earnings mainly reflects target inventors cashing in on their shares.

inventors, where we only keep the years after the merger event and set year -1 to zero (by definition, separation rate is zero for all inventors in year -1).

Panel A shows that the separation rates of target inventors and counterfactual inventors trend similarly following mergers and acquisitions, where the coefficients are statistically insignificant for all periods. This contrasts with previous studies documenting higher departure rates of target firm employees following M&As, especially among key employees like executives (Martin and Mcconnell, 1991; Lagaras, 2019; Kim, 2024). This is likely due to negative effects on inventor mobility predicted by our model being offset by positive effects due to other factors (e.g., poor cultural fit between target employees and the new firm). Panel B of Figure 4 looks at acquirer inventors. M&As have a negative and significant effect on the separation rates of acquirer inventors. The effect grows steadily over time, and acquirer inventors are 10.4% more likely to stay at the acquirer firm than counterfactual inventors five years after the merger. This suggests that inventors are more likely to stay at the same employer when their employer acquires another firm.

Our results suggest that M&As allow acquirer firms to retain more inventors. In Figure 5, we plot the differences in the number of patents assigned to the original employer (employer in year -1) between acquirers' inventors and counterfactual inventors. The coefficients are positive except in the last year, and are statistically significant in the first year after the merger. Inventors at acquirer firms have more patents assigned to the acquirer, despite having a smaller number of patents overall as shown in Figure 1. This is because acquirers' inventors are less likely to move to other firms than counterfactual inventors. Therefore, another benefit from the M&As for the acquirer firms is to retain their inventors and recoup their patents despite lower inventor productivity after the M&As.

4.2 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 counterfactual inventors over time regardless of whether they stay at the merged firms or not. In this section, we decompose the effects of M&As on patenting and earnings between job-movers and job-stayers to analyze 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, $y_t - y_c$, 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.

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 5 to estimate the effects attributed to movers.

Figure 6 summarizes the results from the decomposition for the number of patents. For each period, we plot three bars corresponding to 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, and the difference between movers explains 15–40% of the decline in patenting in year 4 and year 5. In all periods, the part due to differences in separation rates is almost zero. This is because the separation rates of target and counterfactual inventors closely track each other as shown in Figure 4, suggesting that the productivity losses of target inventors are not due to job displacement. Panel B shows that for acquirer inventors, stayers and movers both contribute to the decline in patenting, with stayers explaining a larger part than movers. The lower separation rate of 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).

In Figure 7, we conduct the same decomposition for earnings. Panel A shows that for target inventors, the immediate increase in earnings in the first year is concentrated among stayers. The subsequent decline in earnings is driven predominantly by stayers and to a lesser extent by movers. For example, in year 5, the earnings difference between treated stayers and counterfactual stayers accounts for 72% of the overall earnings difference, whereas the earnings difference between treated movers and counterfactual movers accounts for 27% of the overall earnings difference. In Panel B of Figure 7, we see similar patterns for acquirer inventors, with stayers explaining the majority of the earnings differences and movers explaining a smaller part of the earnings differences. For example, in year 5, the earnings difference between treated stayers and counterfactual stayers explains 78% of the overall earnings difference, and the earnings difference between treated movers and counterfactual movers explains 48% of the overall earnings difference. As in the case of patents, the difference in separation rates does not explain the decline in earnings for target inventors, and contributes to a *increase* in earnings for acquirer inventors, since acquirer inventors have lower separation rates and stayers have higher earnings than movers.

The results from the decomposition indicate that the decline in patenting and earnings among target and acquirer inventors is mostly attributed to the lower earnings and patenting of treated stayers compared to counterfactual stayers. We also see that treated movers (inventors in acquirer or target firms who later move to other firms) have lower earnings and number of patents relative to counterfactual movers. This is consistent with our prediction that inventors have lower incentives and effort levels following M&As, which reduces their earnings and patenting both when they continue to work in the incumbent firm and when they move to other firms.

4.3 Labor Market Competition and the Impact of M&As

The key channel through which M&As reduce inventor productivity is that M&As reduce labor market competition and inventors' rents from successful innovations. The model in Section 1 shows that the extent to which M&As reduce labor market competition depends on inventor's outside options: M&As reduce labor market competition more if similar inventors are concentrated in a small number of firms and inventors have few outside options after the merger.

We measure the level of labor market competition and inventors' outside options using labor market concentration following Arnold (2019). To measure concentration in the labor market for inventors, we use inventors' field specialization, as inventors often 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 particular, we use the technology class of inventors' patents to determine an inventor's field of specialization.[12]

[12] We use 4-digit CPC subclasses, and there are around 600 technology classes in total. If the inventor has patents in multiple technology classes, we use a weighted average of concentration measures across the technology classes.

We split our sample into high-impact inventors, who are more affected by the merger in terms of market power, and low-impact inventors. As shown in Arnold (2019), the impact on market power is larger when the initial level of concentration is high and there is a large increase in concentration due to the merger. We then construct the Herfindahl-Hirschman Index (HHI) for technology class m in year t as follows: $HHI_{mt} = \sum_j s_{jmt}^2$, where s_{jmt} is firm j's market share (in percentages), defined as the number of inventors in technology class m in year t working for firm j divided by the total number of inventors in all firms in technology class m in year t. A merger between two firms with market share s_{jm} and $s_{j'm}$ in the year before the merger would increase the HHI by $\Delta HHI = 2s_{jm}s_{jm}$. Intuitively, a field has higher concentration if all inventors working in that field are concentrated in a few firms, in which case each inventor fewer outside options to move to.[13]

We define high-impact inventors as those who have above-median initial level of HHI in the year before the merger and above-median change in HHI resulting from the merger.[14] We then estimate a variation of regression 5 to compare the effects on high-impact and low-impact inventors:

$$\Delta Y_{ii'js} = \sum_{k \in -5,-4,-3,-2,0,1,2,3,4,5} \left(\gamma_k D_{ijs}^k \times HiImpact_i + \mu_k D_{ijs}^k \times LoImpact_i \right) + \varepsilon_{is}, \tag{7}$$

where $HiImpact_i$ is an indicator for high-impact inventor with above-median initial level of concentration and above-median change in concentration due to the merger. $LoImnpact_i$ is the complement of $HiImpact_i$. Importantly, whether a merger has a high impact on concentration varies at the inventor level. Even within the same firm, a merger may be high-impact for some inventors and low-impact for other inventors.

Figure 8 to Figure 10 plot the differential effects of high-impact and low-impact mergers

[13] We do not define local labor markets and instead treat all inventors in a certain field across all locations as in the same market. This is because inventors are high-skilled workers and more mobile than the average worker (Moretti and Wilson, 2017; Akcigit et al., 2022; Amior, 2024), and we observe a lot of cross-commuting-zone and cross-state movements for inventors in the data.

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

on inventors' patenting, earnings, and separation rates. Panel A of each figure reports the estimates for target inventors. Figure 10 shows that the separation rates increase for low-impact target inventors and decrease for high-impact target inventors following M&As. Panel A of Figure 8 shows large negative effects for high-impact target inventors and insignificant effects for low-impact target inventors, consistent with the merger having a larger negative effect on labor market competition and inventor effort when inventors face worse outside options. Panel A of Figure 9 shows similar earnings trajectories for high-impact and low-impact target inventors. While high-impact target inventors reduce their effort more, they are also more likely to stay with the merged firm (as shown in Figure 10), which dampens the negative effect on earnings since job separations are usually associated with earnings losses. The higher separation rates of low-impact inventors may be due to a poor fit (e.g., culture clash) between the target inventors and the acquirer firm (Kim, 2024). The higher separation rates of low-impact inventors and lower separation rates of high-impact inventors together explain the overall null effect on the separation rates of target inventors in Figure 4.

Panel B of Figure 8 to Figure 10 reports the estimates for acquirer inventors. Aligning with the labor market competition channel, we see larger declines in the number of patents, earnings, and separation rates among high-impact inventors. Therefore, when M&As enhance the labor market power of the acquirer firm, their existing inventors have worse outside options, are more likely to stay with the firm, and have lower productivity and earnings.

Table 3 reports the static estimates when we aggregate all post-treatment periods. One concern is that high-impact mergers may happen in certain firms or lead to other firm-level changes. For example, if firms benefit more from high-impact mergers, they may invest more in R&D, which can confound the effects of labor market power. To address this concern, we add firm fixed effects to compare high-impact and low-impact inventors within the same firm. In some specifications, we further include firm-by-commuting zone fixed effects to control for shocks to inventors in the same location and the same firm. Table 3 shows that our results are robust to the inclusion of firm and firm-by-commuting zone fixed effects. Even with the most stringent specification, high-impact target inventors have lower patenting and separation rates, whereas high-impact acquirer inventors have lower patenting, earnings, and separation rates.

4.4 Product Market Competition and Synergy

Our model predicts that the effects of mergers on inventors' productivity and earnings also depend on product market competition and innovation synergy. First, when the product market is less competitive, inventors earn more rents under stand-alone firms, and M&As have a larger negative effect on inventor incentives. We test this empirically by comparing inventors in target or acquirer firms in high-concentration industries with target or acquirer firms in low-concentration industries. We measure industry concentration using the Herfindahl-Hirschman Index (HHI) based on firm sales at the 4-digit NAICS level. Importantly, there is almost zero correlation between industry concentration and inventor labor market concentration, since product market competitors may not innovate in the same technology fields and firms innovating in the same fields may not be product market competitors (Bloom et al., 2013).

Second, our model predicts that M&As have a less negative effect on inventor effort if innovation synergy is higher. To measure this synergy between the target and acquirer firms, we analyze the textual similarity of their patent portfolios prior to the merger. Specifically, we extract the topical content from their historical patents and evaluate the overlap in their stock of technological knowledge using textual analysis. A higher degree of similarity suggests that the firms have aligned technological efforts and share complementary innovation capabilities, which can enhance collaboration and create synergy post-merger. We describe the details of our measure in the Appendix.

The results are consistent with the theory predictions (results are currently under review for disclosure and will be added in one to two months).

5 Robustness and Discussion

In this section, we first consider failed mergers as a placebo test of our results. We then consider alternative explanations for our findings. Finally, we discuss the broader implications of our results for mergers and innovation.

5.1 Failed Mergers

A causal interpretation of our results requires that inventors in treated and control firms would have similar trends in patenting and earnings. Although we observe no pre-trends in treated firms, firms may choose to merge when they expect a slowdown in innovation, which may explain the decline in patenting afterwards. To address this concern, we consider a sample of 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 industry dynamics, making them a useful quasi-control group, representing what might have happened in the absence of a completed merger.

We identify the failed mergers as those with status "Pending" 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 the Appendix.

Using the sample of inventors from failed mergers and the same empirical strategy as our main analysis, we find no statistically significant effects on their patenting productivity or earnings (results under review for disclosure). This alleviates the concern that the observed negative effects of mergers on patenting and earnings are due to the selection of firms that choose to merge.

5.2 Firm Investment

In our model, we assume that inventor effort is the only input to innovation. In the Appendix, we consider a more realistic setting in which firms also need to invest in order to innovate. We show that when the economies of scale are limited, the merged firm finds it optimal to fire one inventor to cut duplicate costs. Therefore, allowing for firm investment further amplifies the negative effect on inventors' patenting productivity and earnings.

More generally, mergers can allow firms to internalize business-stealing effects and lower incentives to innovate for the merged firm when the target and acquirer firms compete neck-to-neck (Aghion et al., 2005; Federico et al., 2017, 2020). If firm investments and inventor efforts are complements, a reduction in firm investments can lead to a reduction in inventors' patenting productivity and earnings.

Although a decrease in firms' incentives to innovate can also contribute to the negative effect of M&As on inventor productivity and earnings, several findings suggest that changes in inventor incentives to innovate due to labor market power still play an important role in our setting. First, if the merged firm scales down or cuts investments and there is no change in labor market competition, inventors should benefit from leaving the merged firm and innovating elsewhere before exerting efforts. Federico et al. (2017) show that while mergers reduce innovation incentives of merging firms, they tend to increase innovation incentives of other firms in the industry. Therefore, a reduction in firm investments alone without changes in labor market power should lead to more inventor separations, which is opposite to what we find. Second, we find that inventors moving away from target and acquirer firms also patent less than counterfactual movers, which is unlikely to be explained by lower investment at the merged firm. Third, we should expect stronger business-stealing effects and a larger decrease in firms' incentives to innovate when the two merged firms compete in the same product market. However, we find similar effects for mergers between firms that are not product market rivals (results under review for disclosure), suggesting that internalization of business stealing effects does not explain all of our results.

5.3 Alternative Explanations

5.3.1 Value-Destroying Mergers

Another potential explanation for our findings is that mergers destroy value and reduce workers' productivity and earnings. While the channels in our paper also apply to non-inventor workers, we find no significant change in sales per worker or earnings per worker at the target or acquirer firms (results under review for disclosure). Therefore, the decrease in productivity and earnings is much more pronounced for inventors. 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' efforts are sensitive to monetary rewards (Bernstein et al., 2021) and inventors get a lot of rents from their innovation (Kline et al., 2019), so M&As could have a larger effect on their rents and incentives.

5.3.2 Synergy and Consolidation

Efficiency gains through synergies in product markets or labor markets are often argued as the main motivation of merger activities (Hoberg and Phillips, 2010; Tate and Yang, 2023). Bena and Li (2014) find that innovation output increases following mergers when there is pre-merger technological overlap between merging firms. Li and Wang (2023) show that a key mechanism for achieving synergy is collaboration between acquirer and target inventors, which leads to more radical, impactful, and valuable patents. However, this is an implausible explanation for our results given overall negative effect on patenting and earnings.

Relatedly, the merged firm may optimally choose to shut down the unpromising innovation projects and focus on more promising ones. This could explain the lower patenting and earnings of inventors with unpromising projects. However, we still see a decline in the number of high-citation patents and a reduction in patenting and earnings for highly-cited inventors, which is unlikely to be caused by consolidation of innovation projects.

5.3.3 Outsourcing Innovation

Another possibility is that firms acquire other innovative firms to outsource innovation and replenish their research pipeline. This could occur when firms experience a decline in their internal R&D productivity (Higgins and Rodriguez, 2006; Ma, 2020). It can also arise in an equilibrium where large firms optimally decide to let small firms conduct R&D and then subsequently acquire the successful innovators (Phillips and Zhdanov, 2013). A number of papers document "acqui-hiring", where firms engage in acquisitions to obtain skilled employees of the target firms like the inventors (Ouimet and Zarutskie, 2020; Beaumont et al., 2019), although it may fail because the acquired workers often have higher turnover rates than regular hires (Kim, 2024).

If acquirer firms acquire key inventors from the target firms and outsource innovation, we should expect M&As to lead to a lower number of patents by acquirer inventors, as the acquirer firms gain access to successful innovations through the acquisitions instead of investing in R&D themselves. However, the negative effect of M&As on the patenting and earnings of target inventors contradicts this channel because inventors at target firms should produce more patents when the acquirer firm outsources innovation to the target firm. The earnings of target inventors should also go up as the acquirer firms try to retain the valuable inventors. Furthermore, acquirer inventors are not less productive and in fact slightly more productive than target inventors in our data. Overall, these results do not support an innovation outsourcing explanation.

5.4 Welfare Implications

We have shown that M&As increase firms' labor market power and reduce inventors' incentives to innovate. How does this affect welfare?

Our simple theory from Section 1 sheds light on this question. The theory implies social costs and as well as benefits from M&As. By reducing ex-ante inventor effort, M&As reduce the innovation outputs in the economy, which could harm economic growth and consumer surplus. By creating innovation synergies and economies of scale (in the case with firm investment), M&As can potentially improve innovation efficiency and increase total surplus from innovation. Whether M&As improve or reduce overall welfare depends on these effects' magnitudes and the weights placed on firm profits versus inventor and consumer surplus. A comprehensive welfare analysis would also need to take into account technological spillovers from innovation and product market competition. As a result, a full welfare analysis is beyond the scope of this paper, but two points are worthy of discussion.

First, M&As have a long-lasting negative impact on inventors' careers. The lower productivity and earnings do not revert after five years, and inventors have lower productivity and earnings even after they move to other firms. Inventors early in their careers experience larger losses. Furthermore, lower monetary rewards and reduced exposure to successful inventors may affect career choices and deter workers from becoming inventors (Bell et al., 2019). These results suggest that M&As can potentially reduce the supply and long-term productivity of inventors, which will add to the negative welfare impact of M&As.

Second, innovative firms get higher surplus from increased labor market power because they can pay inventors less and have lower inventor turnovers. Innovative startups also benefit from the prospect of exit through acquisition by incumbent firms (Phillips and Zhdanov, 2013). In our model, the amount of firm investment is fixed and there is no firm entry. However, it is plausible that M&As may increase ex-ante entrepreneurship entry and firm investment in innovation, which may have a countervailing positive effect on welfare.

6 Conclusion

This paper examines how mergers and acquisitions impact innovation by focusing on their effects on inventors. Through a theoretical model and empirical analysis of individual-level administrative data, we demonstrate that M&As enhance firms' labor market power and diminish inventors' incentive to innovate, leading to lower patenting productivity, earnings, and job mobility for inventors in both the target and acquirer firms. Alternative interpretations, such as value-destroying acquisitions, consolidation, and innovation outsourcing do not explain our results.

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 consider the effects on innovation. Our findings suggest that labor market power over innovative labor and reduced innovation incentives of inventors should be an important consideration when evaluating the impact of mergers on innovation.

While our paper studies inventors, the same mechanism could also apply to other high-skilled labor. Since high-skilled labor is more concentrated within particular industries than low-skilled labor (Nimczik, 2020), mergers may contribute to the rising labor market power of firms that employ high-skilled labor documented in Seegmiller (2021). Our paper implies that increasing labor market power may be an important motive for "acqui-hiring" mergers besides obtaining high-skilled employees, but firms need to trade off potential negative effects on employee incentives.

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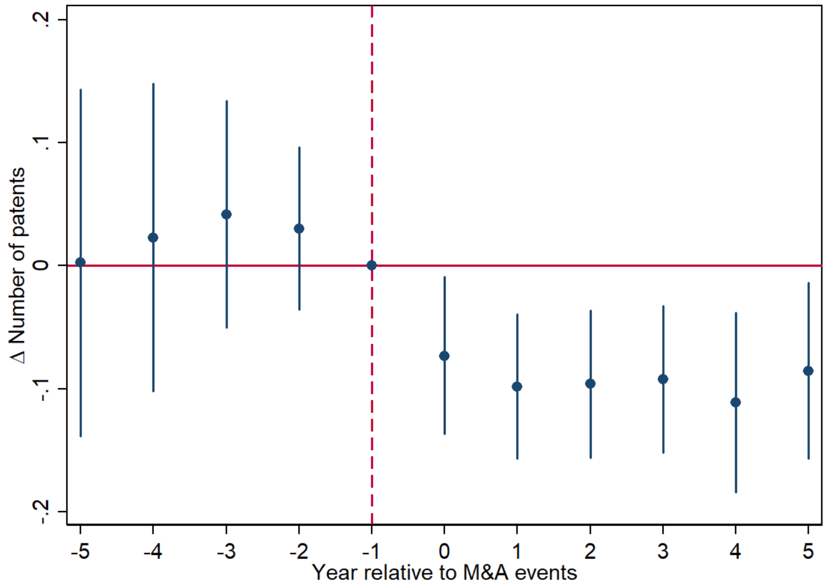
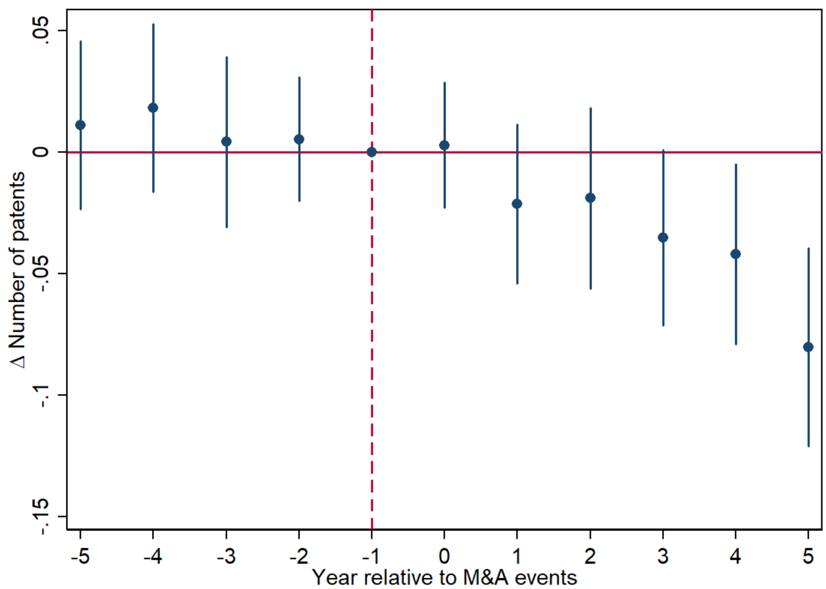
Figure 1: The Impact of M&As on the Number of Patents



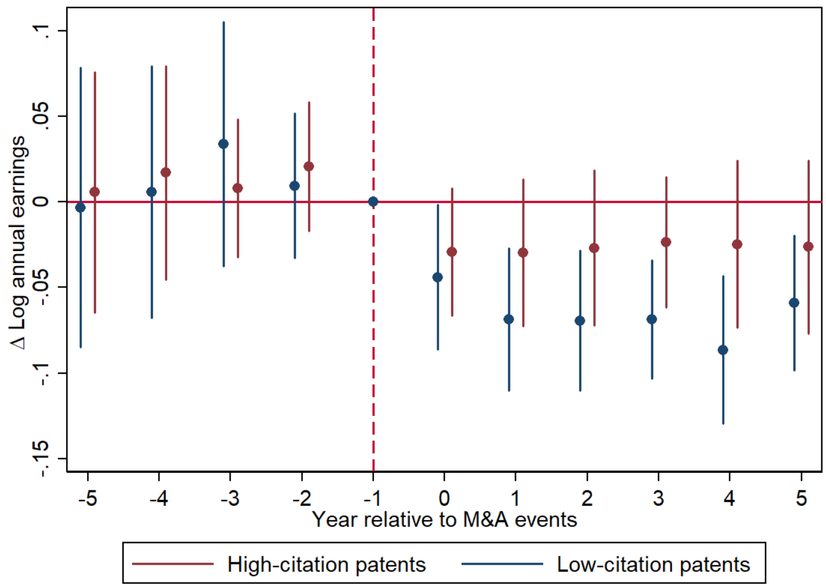
Panel A: Target Inventors



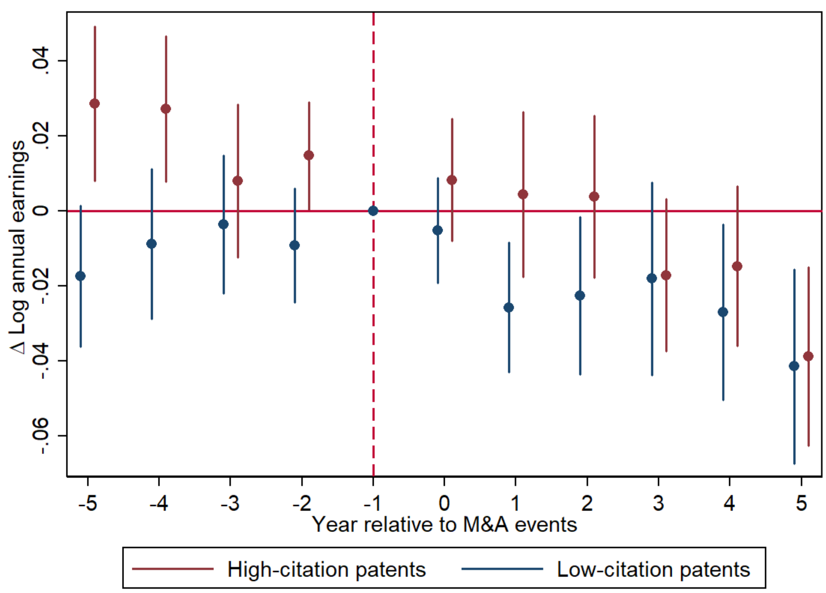
Panel B: Acquirer Inventors

This figure plots the event-study estimates for the impact of M&As on the number of granted patents applied by inventors based on equation 5. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 2: The Impact of M&As on the Number of High-Citation and Low-Citation Patents



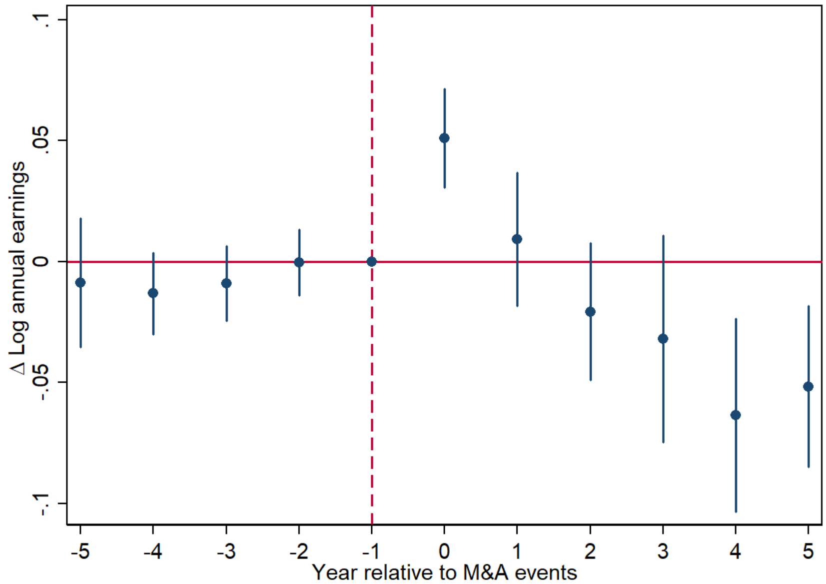
Panel A: Target Inventors



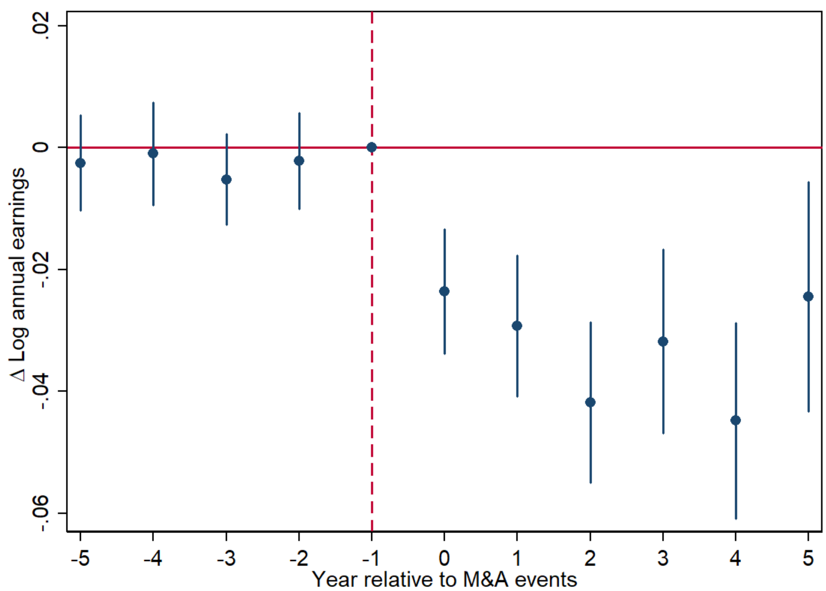
Panel B: Acquirer Inventors

This figure plots the event-study estimates for the impact of M&As on the number of granted patents with high citations (red lines) or with low citations (blue lines) applied by inventors based on equation 5. We define high-citation patents as those with above-median citations in a year, and low-citation patents as those with below-median citations. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 3: The Impact of M&As on Inventors' Earnings



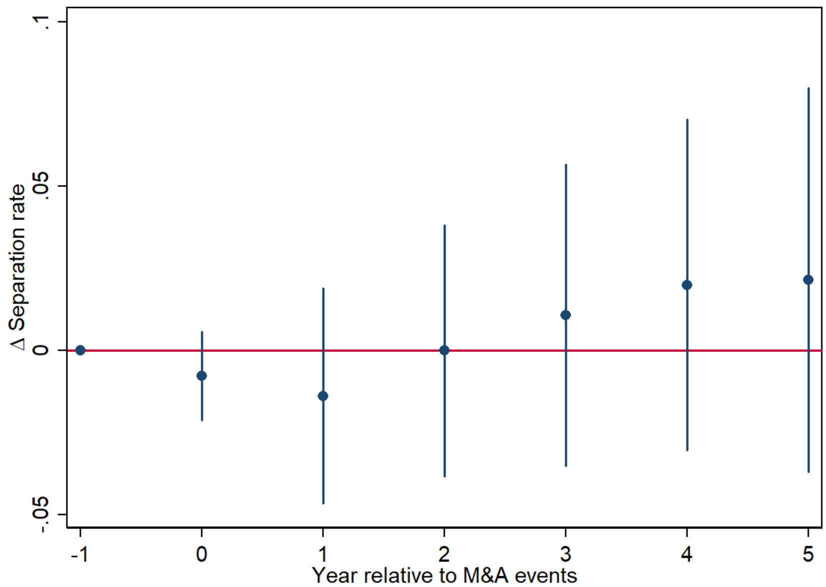
Panel A: Target Inventors



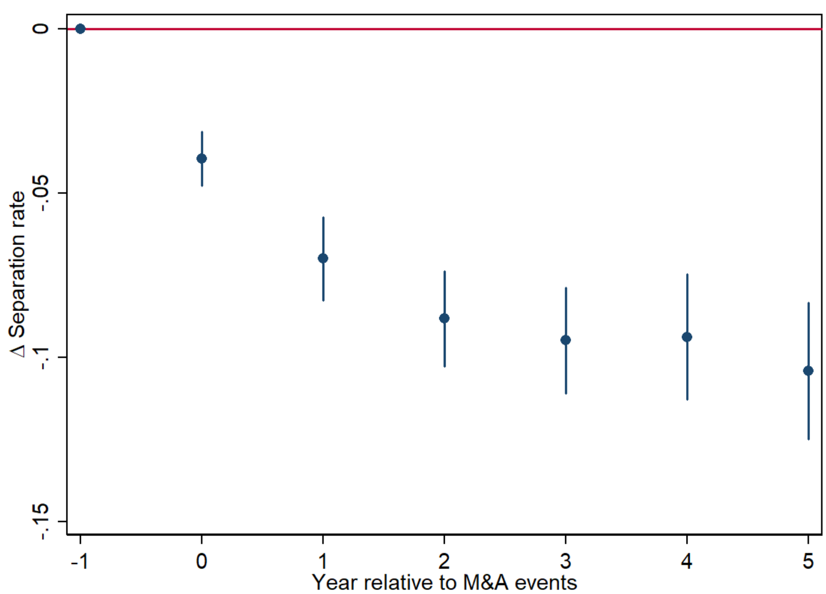
Panel B: Acquirer Inventors

This figure plots the event-study estimates for the impact of M&As on the annual earnings of inventors based on equation 5. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 4: The Impact of M&As on Inventors' Separation Rates



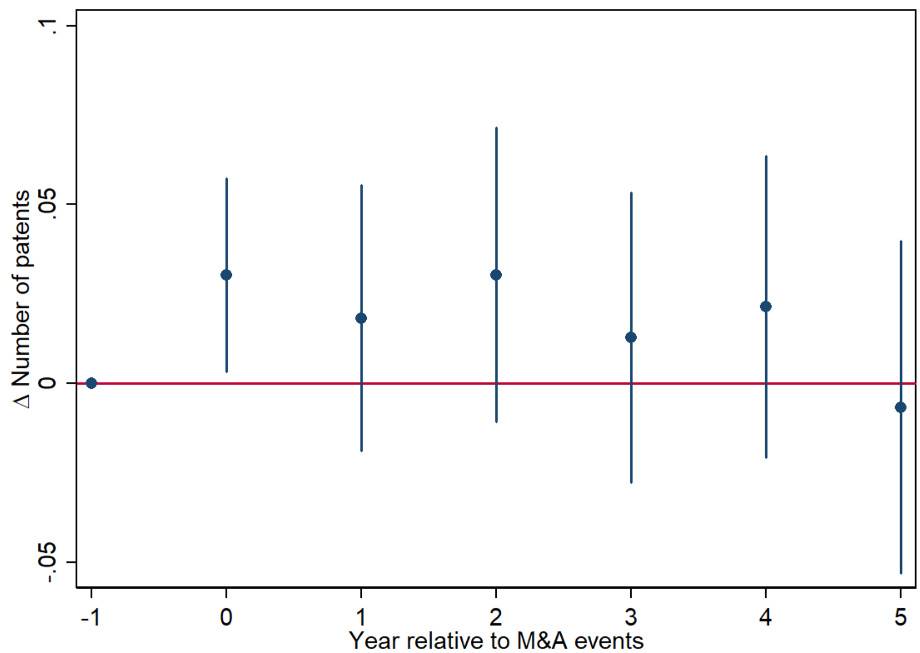
Panel A: Target Inventors



Panel B: Acquirer Inventors

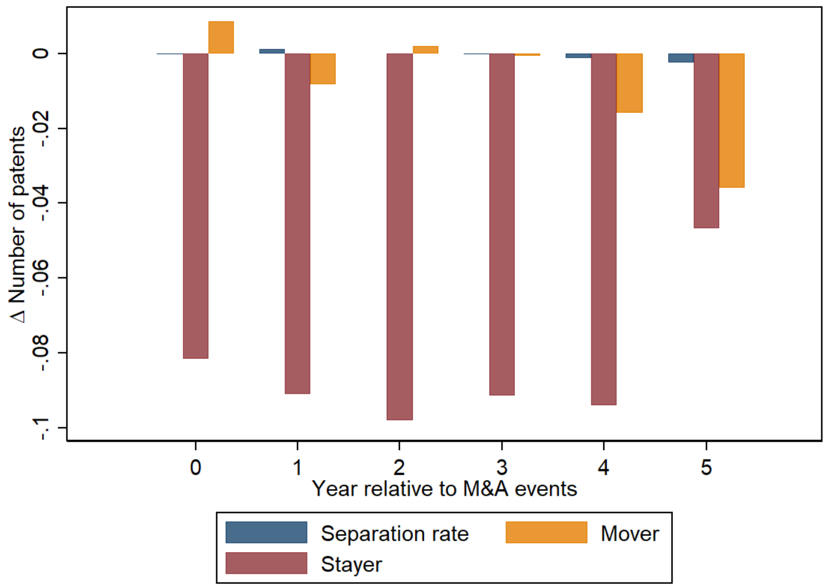
This figure plots the event-study estimates for the impact of M&As on the separation rate of inventors based on equation 5. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. We define the separation rate as whether the inventor is no longer employed by the dominant employer in year -1. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 5: The Impact of M&As on the Number of Patents Belonging to the Acquirer

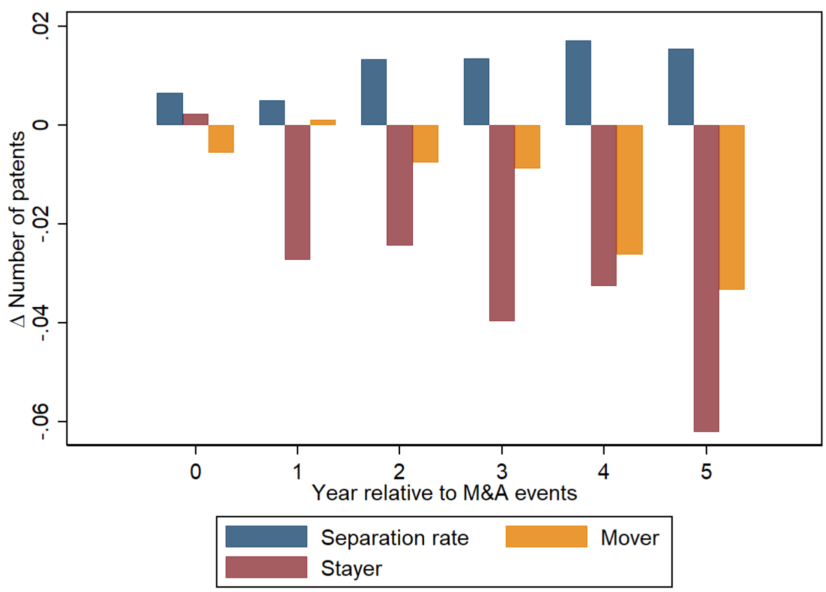


This figure plots the event-study estimates for the impact of M&As on the number of granted patents applied by acquirers' inventors that belong to the original firm at year $t-1$ based on equation 5. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 6: Decomposition of the Impact on Patents Between Stayers and Movers



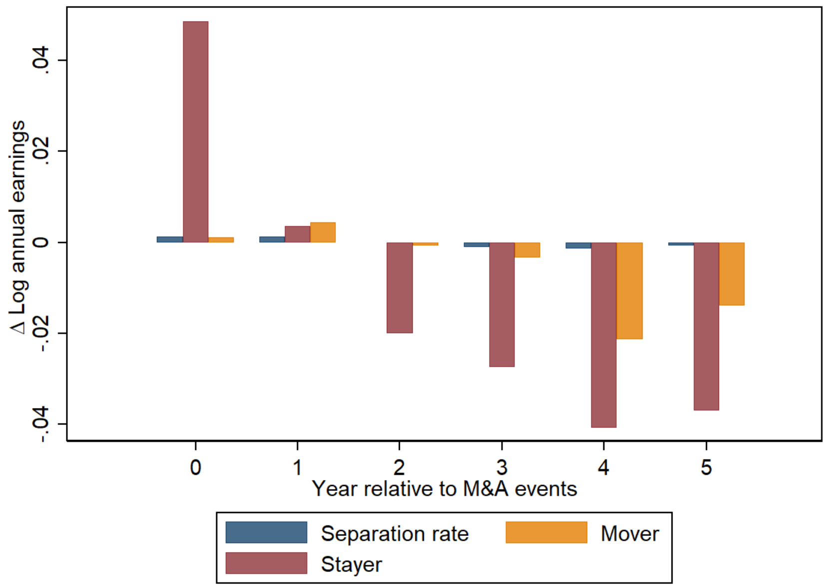
Panel A: Target Inventors



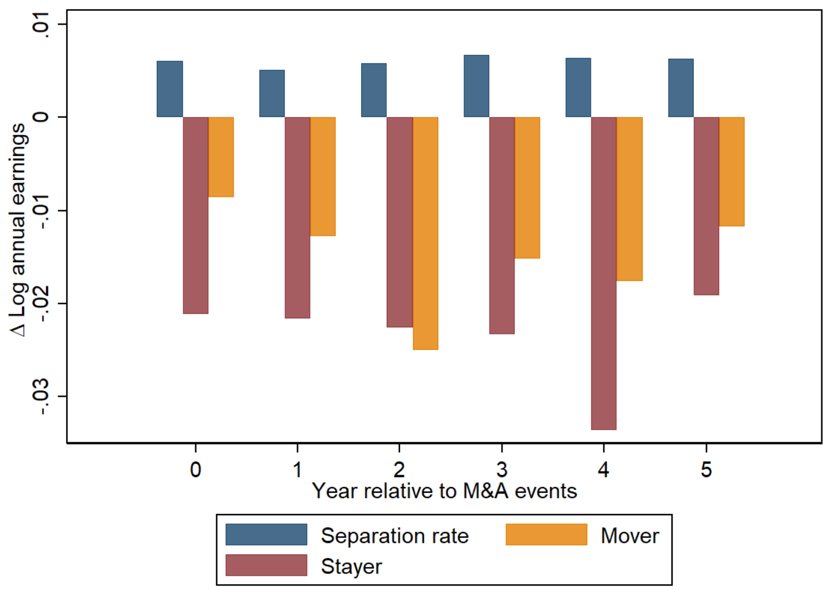
Panel B: Acquirer Inventors

This figure plots the decomposition for the impact of M&As on the number of granted patents applied by inventors based on equation 6. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The coefficient is normalized to be zero in year -1. The red bars represent the effects for stayers, the yellow bars represent the effects for movers and the blue bars represent the effects due to changes in separation rates.

Figure 7: Decomposition of the Impact on Earnings Between Stayers and Movers



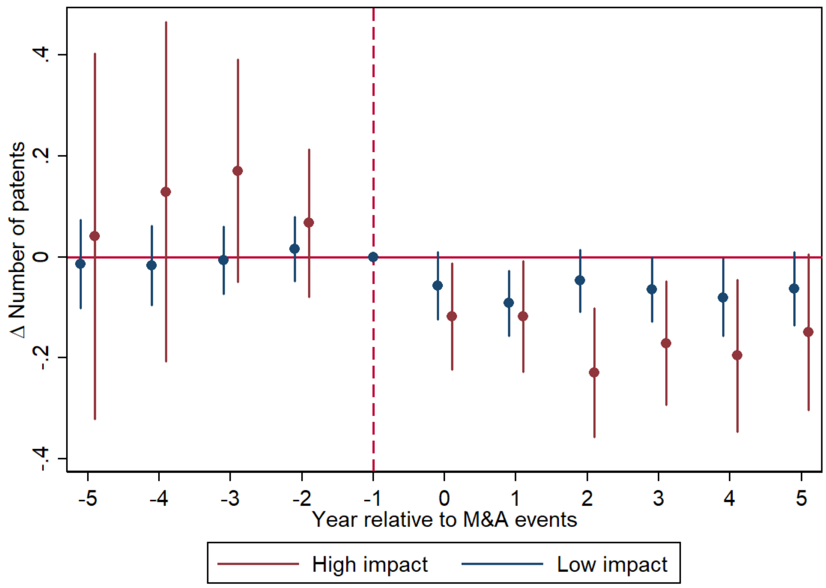
Panel A: Target Inventors



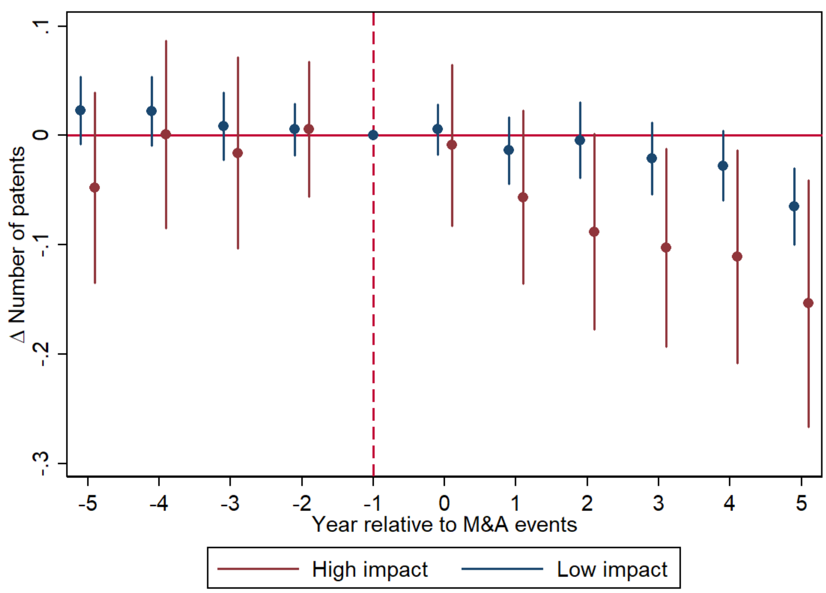
Panel B: Acquirer Inventors

This figure plots the decomposition for the impact of M&As on the annual earnings of inventors based on equation 6. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The coefficient is normalized to be zero in year -1. The red bars represent the effects for stayers, the yellow bars represent the effects for movers and the blue bars represent the effects due to changes in separation rates.

Figure 8: The Impact of M&As on the Number of Patents for High-Impact and Low-Impact Inventors



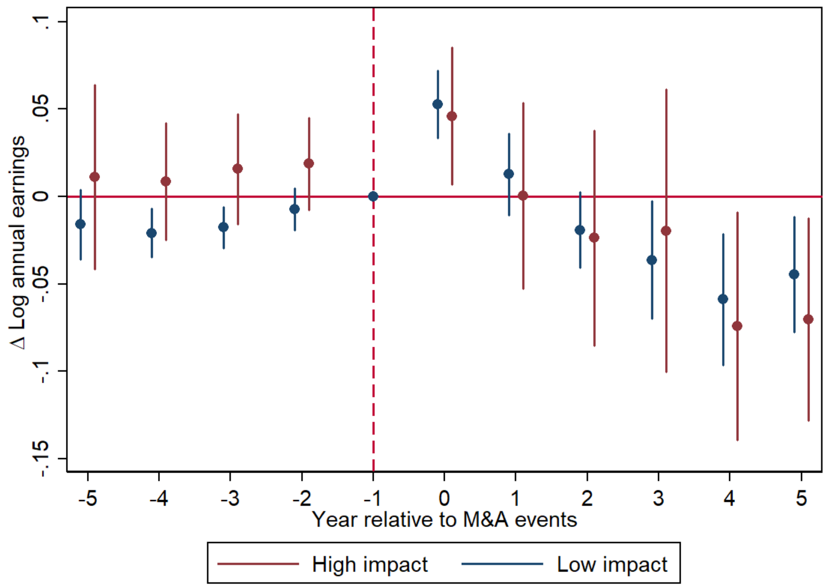
Panel A: Target Inventors



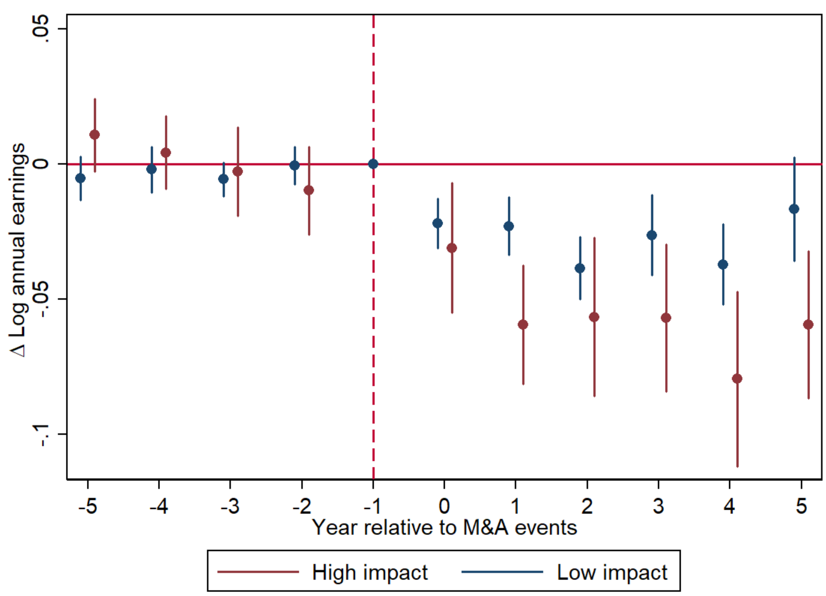
Panel B: Acquirer Inventors

This figure plots the event-study estimates for the impact of M&As on the number of granted patents applied by high-impact and low-impact inventors based on equation 7. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The red (blue) plots indicate inventors experiencing M&As with a high impact (low impact) on labor market concentration. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 9: The Impact of M&As on Earnings for High-Impact and Low-Impact Inventors



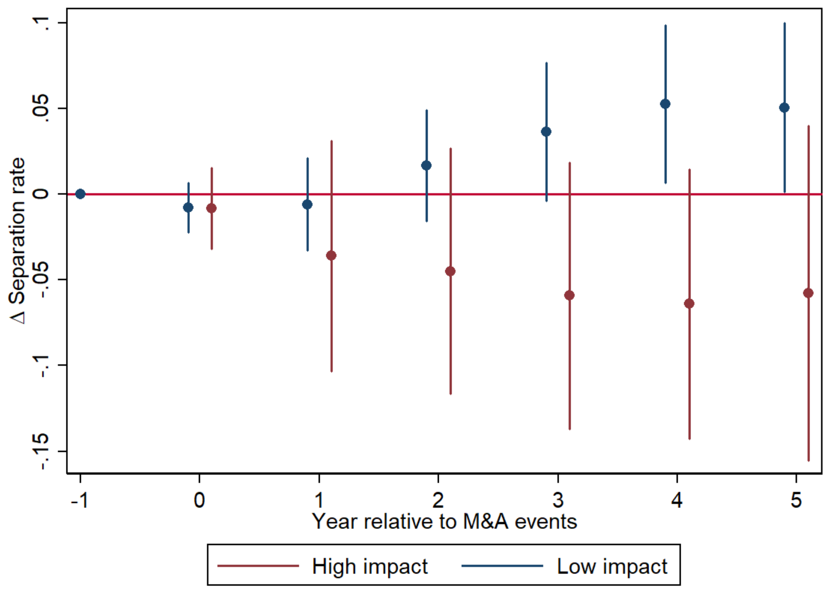
Panel A: Target Inventors



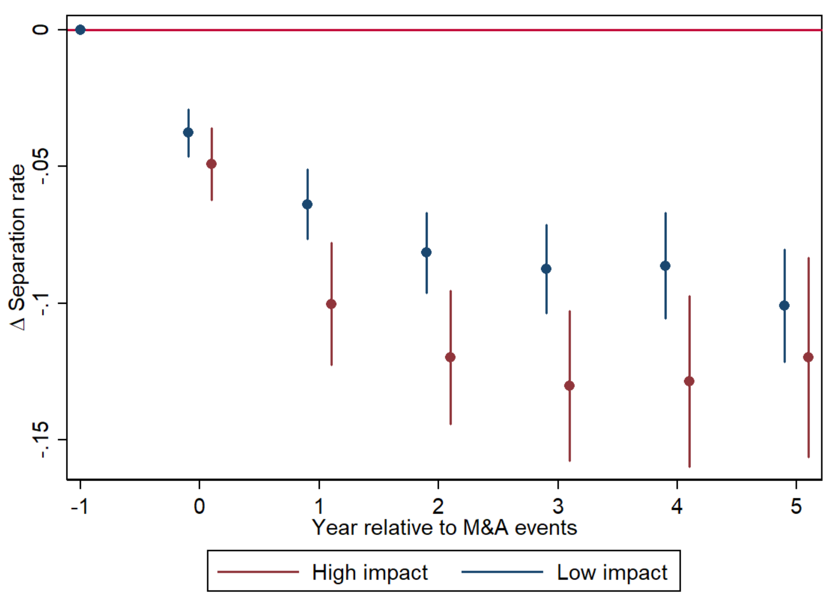
Panel B: Acquirer Inventors

This figure plots the event-study estimates for the impact of M&As on the annual earnings of high-impact and low-impact inventors based on equation 7. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The red (blue) plots indicate inventors experiencing M&As with a high impact (low impact) on labor market concentration. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Figure 10: The Impact of M&As on Separation Rates for High-Impact and Low-Impact Inventors



Panel A: Target Inventors



Panel B: Acquirer Inventors

This figure plots the event-study estimates for the impact of M&As on the separation rates of high-impact and low-impact inventors based on equation 7. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The red (blue) plots indicate inventors experiencing M&As with a high impact (low impact) on labor market concentration. We define the separation rate as whether the inventor is no longer employed by the dominant employer in year -1. The coefficient is normalized to be zero in year -1. The lines indicate 95 percent confidence intervals where the standard errors are clustered at the firm-event level.

Table 1: Summary Statistics

Panel A: Target Inventors

		Treated inventors		Control inventors	
	N	Mean	Std dev	Mean	Std dev
Age	160000	45.52	9.002	45.61	9.080
Log annual earnings	160000	12.00	0.7051	12.00	0.7034
Annual earnings	160000	251400	1909000	243000	1311000
Job switching rate	160000	0.1650	0.3712	0.1459	0.3530
Separation rate	96000	0.1889	0.3914	0.1870	0.3899
Number of patents	160000	0.6722	1.835	0.6436	1.492
Number of high-citation patents	160000	0.3298	1.084	0.3392	0.9920
Number of low-citation patents	160000	0.3423	1.097	0.3044	0.8408
Number of persons	21500				
Number of firms	3300				

Panel B: Acquirer Inventors

		Treated inventors		Control inventors	
	N	Mean	Std dev	Mean	Std dev
Age	2210000	45.30	9.005	45.30	8.918
Log annual earnings	2210000	11.93	0.6276	11.95	0.6552
Annual earnings	2210000	209200	840800	228000	1214000
Job switching rate	2210000	0.1050	0.3065	0.1366	0.3435
Separation rate	1353000	0.1169	0.3213	0.1788	0.3832
Number of patents	2210000	0.6828	2.041	0.6290	1.538
Number of high-citation patents	2210000	0.3310	1.187	0.3388	1.027
Number of low-citation patents	2210000	0.3518	1.163	0.2902	0.8335
Number of persons	109000				
Number of firms	3300				

This table provides summary statistics for the variables used in the paper on the matched sample of 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 3. The number of observations is rounded in accordance with the disclosure rules set by the U.S. Census Bureau.

Table 2: The Impact of M&As on Inventor Outcomes

Panel A: Target Inventors

	Δ Number of patents	Δ Log annual earnings	Δ Separation rate	Δ Number of high-citation patents	Δ Number of low-citation patents
	(1)	(2)	(3)	(4)	(5)
Post	-0.0969***	-0.0275*	0.0053	-0.0264	-0.0705***
	(0.0282)	(0.0154)	(0.0204)	(0.0205)	(0.0167)
Obs	160000	160000	160000	160000	96000

Panel B: Acquirer Inventors

	Δ Number of patents	Δ Log annual earnings	Δ Separation rate	Δ Number of high-citation patents	Δ Number of low-citation patents
	(1)	(2)	(3)	(4)	(5)
Post	-0.0362**	-0.0345***	-0.0886***	-0.0102	-0.0260***
	(0.0065)	(0.0157)	(0.0074)	(0.0094)	(0.0095)
Obs	2210000	2210000	2210000	2210000	1353000

This table reports the impact of M&As on inventor outcomes. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The *Post* dummy indicates the years after the the M&A event. In column 1, the dependent variable is the number of patents applied by the inventor in a given year. In column 2, the dependent variable is log annual earnings. In column 3, the dependent variable is separation rate, defined as whether the inventor is no longer employed by the dominant employer in year -1. In column 4, the dependent variable is the number of patents with above-median forward citations. In column 5, the dependent variable is the number of patents with below-median forward citations. The coefficient is normalized to be zero in year -1. 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: The Impact of M&As for High-Impact vs Low-Impact Inventors

Panel A: Target Inventors

	Δ Number of patents			Δ Log annual earnings			Δ Separation rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post × High Impact	-0.1619***	-0.0899**	-0.0830**	-0.0241	-0.0079	-0.0033	-0.0771**	-0.0411**	-0.0339*
	(0.0498)	(0.0406)	(0.0389)	(0.0208)	(0.0145)	(0.0156)	(0.0311)	(0.0177)	(0.0187)
FE	No	Firm FE	Firm×CZ FE	No	Firm FE	Firm×CZ FE	No	Firm FE	Firm×CZ FE
Obs	160000	160000	160000	160000	160000	160000	96000	96000	96000

Panel B: Acquirer Inventors

	Δ Log annual earnings			Δ Number of patents			Δ Separation rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post × High Impact	-0.0551**	-0.0564**	-0.0533*	-0.0338***	-0.0322***	-0.0316***	-0.0316***	-0.0275***	-0.0257***
	(0.0274)	(0.0279)	(0.0279)	(0.0091)	(0.0093)	(0.0093)	(0.0097)	(0.0085)	(0.0083)
FE	No	Firm FE	Firm×CZ FE	No	Firm FE	Firm×CZ FE	No	Firm FE	Firm×CZ FE
Obs	2210000	2210000	2210000	2210000	2210000	2210000	1353000	1353000	1353000

This table reports the differential effect for high-impact vs low-impact M&As on the inventor outcomes. Panel (a) and (b) show the estimates for the effects on target inventors and acquirer inventors respectively. The *Post* dummy indicates the years after the M&A event. The *High Impact* dummy indicates M&As with a high impact on labor market concentration. In columns 1 to 3, the dependent variable is the number of patents applied by the inventor in a given year. In columns 4 to 6, the dependent variable is log annual earnings. In columns 7 to 9, the dependent variable is separation rate, defined as whether the inventor is no longer employed by the dominant employer in year -1. Columns 2, 5, and 8 include firm fixed effects (where firm is the dominant employer in year $t-1$), and column 3, 6, and 9 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).

Online Appendix

A. Theory Appendix

A.1. Proofs

Lemma 1. It is optimal for the post-merger firm to have two inventors.

Proof of Lemma 1. If the merged firm only keeps one inventor, the inventor's expected payoff is:

$$e_i^{M'}(v+\beta(1-v))M - \frac{k}{2}(e_i^{M'})^2.$$

The optimal effort level of the employee is:

$$e_i^{M'*} = \frac{(v+\beta(1-v))M}{k}.$$

The firm's expected profit is:

$$\pi^{M'*} = (1-\beta)(1-v)e_i^{M'*}M = \frac{(1-\beta)(1-v)(v+\beta(1-v))M^2}{k}.$$

From Equation (4) we get that firm's expected profit when there is low synergy ($r \leq v$) is:

$$\pi^{M*} = (1-v)(v+\beta(1-v))M^2 \frac{(\beta-(1-\beta)v)M + 2(1-\beta)k}{(k+\beta(1-v)M)^2}.$$

The difference between π^{M*} and $\pi^{M'*}$ is:

$$\frac{\pi^{M*}-\pi^{M'*}}{(1-v)(v+\beta(1-v))M^2} = \frac{(1-\beta)k^2-(1-\beta)\beta^2(1-v)^2M^2-[2\beta(1-\beta)(1-v)+(1-\beta)v-\beta]Mk}{(k+\beta(1-v)M)^2k}$$

Since $k > M$, $(1-\beta)k^2-(1-\beta)\beta^2(1-v)^2M^2 > (1-\beta)[1-\beta^2(1-v)^2]k^2$, and we show below that $(1-\beta)[1-\beta^2(1-v)^2] > 2\beta(1-\beta)(1-v)+(1-\beta)v-\beta$, therefore $(1-\beta)k^2-(1-\beta)\beta^2(1-v)^2M^2-[2\beta(1-\beta)(1-v)+(1-\beta)v-\beta]Mk > (1-\beta)[1-\beta^2(1-v)^2]k^2-[2\beta(1-\beta)(1-$

$v) + (1-\beta)v - \beta]Mk > (1-\beta)[1-\beta^2(1-v)^2]Mk - [2\beta(1-\beta)(1-v) + (1-\beta)v - \beta]Mk > 0$, and $\pi^{M*} - \pi^{M'*} > 0$.

We now show that $(1-\beta)[1-\beta^2(1-v)^2] > 2\beta(1-\beta)(1-v) + (1-\beta)v - \beta$. Rearrange and we get:

$$(1-\beta)(1-v)[1-\beta^2(1+v)-2\beta] > -\beta$$

Denote $\Phi(v) = (1-\beta)(1-v)[1-\beta^2(1+v)-2\beta]$. Take derivative w.r.t. v:

$$\Phi'(v) = (1-\beta)(2\beta^2 v - (1-2\beta)).$$

When $\beta \geq \frac{1}{2}$, $\Phi'(v) \geq 0$, and $\Phi(v) \geq \Phi(0) = (1-\beta)(1-\beta^2-2\beta) > -0.27 > -\beta$.

When $\beta \leq \frac{\sqrt{3}-1}{2}$, $\Phi'(v) \leq 0$, and $\Phi(v) \geq \Phi(1) = 0 > -\beta$.

When $\frac{\sqrt{3}-1}{2} < \beta < \frac{1}{2}$, $\Phi(v) \geq \Phi(\frac{1-2\beta}{2\beta^2}) = -(1-\beta)(1-\frac{1}{2\beta}+\beta)^2 > -\frac{1}{4}(1-\beta) > -\frac{1}{4} > -\beta$.

Proof of Proposition. From equation (2) and equation (4), $e^{M*} < e^{S*}$ if and only if:

$$\frac{(v+\beta(1-v))M}{k+\beta(1-v-(r-v)^+)M} < \frac{(\delta+\beta(1-\delta))M}{k+(\delta+\beta(1-\delta)-d)M}$$

Rearranging and we get:

$$d > \frac{(v+(r-v)^+ - (1-\beta)(1-v))\,(\delta+\beta(1-\delta)) - (1-\beta)(\delta-v)k/M}{v+\beta(1-v)} \equiv d_0$$

Given that we have $d \geq 0$, it follows that $e^{M*} < e^{S*}$ if and only if $d > \max\{d_0, 0\}$.

Proof of Corollary 1. If $r \leq d$, then given $k > M$ and $d < 1$, we have

$$d_0 = \frac{(v+(r-v)^+ - (1-\beta)(1-v))\,(\delta+\beta(1-\delta)) - (1-\beta)(\delta-v)k/M}{v+\beta(1-v)}$$

$$< \frac{(d-(1-\beta)(1-v))\,(\delta+\beta(1-\delta)) - (1-\beta)(\delta-v)k/M}{v+\beta(1-v)}$$

$$< \frac{d(\delta + \beta(1-\delta)) - (1-\beta)(\delta - v)}{v + \beta(1-v)} = d + \frac{(1-\beta)(\delta - v)(d-1)}{v + \beta(1-v)} < d.$$

Then it follow from the Proposition that $e^{M*} < e^{S*}$.

Proof of Corollary 2. From equation (2), it is straightforward to show that $\partial e^{S*}/\partial v = \partial e^{S*}/\partial r = 0$, and $\partial e^{S*}/\partial d > 0$.

From equation (4), it is straightforward to show that $\partial e^{M*}/\partial d = 0$.

When $r > v$, $e^{M*} = \frac{(v+\beta(1-v))M}{k+\beta(1-r)M}$, thus $\partial e^{M*}/\partial v > 0$ and $\partial e^{M*}/\partial r > 0$.

When $r \leq v$, $e^{M*} = \frac{(\beta+v(1-\beta))M}{k+\beta(1-v)M}$, thus $\partial e^{M*}/\partial v > 0$ and $\partial e^{M*}/\partial r = 0$.

As a result, we have:

$$\partial\beta^e/\partial v = \partial e^{M*}/\partial v - \partial e^{S*}/\partial v > 0$$

$$\partial\beta^e/\partial d = \partial e^{M*}/\partial d - \partial e^{S*}/\partial d < 0$$

$$\partial\beta^e/\partial r = \partial e^{M*}/\partial r - \partial e^{S*}/\partial r \geq 0$$

Proof of Corollary 3. Under the stand-alone structure, the inventor's expected payoff is:

$$w^{S*} = (e^{S*})^2 dM + e^{S*}(1-e^{S*})(\delta + \beta(1-\delta))M - \frac{k}{2}(e^{S*})^2 = \frac{k}{2}(e^{S*})^2$$

Similarly, the expected payoff under merger is $w^{M*} = \frac{k}{2}(e^{M*})^2$.

Therefore $\partial\beta^w/\partial x = \partial w^{M*}/\partial x - \partial w^{S*}/\partial x = k(\partial e^{M*}/\partial x - \partial e^{S*}/\partial x) = k(\partial\beta^e/\partial x)$ for $x = (v, d, r)$.

From Corollary 3 we get that $\partial\beta^w/\partial v > 0$, $\partial\beta^w/\partial d < 0$, and $\partial\beta^w/\partial r \geq 0$.

A.2. Model With Firm Investment in Innovation

In this section, we extend our model such that firms need to make an initial investment before their inventors exert effort. Specifically, at $t = 0$, if the two firms operate stand-alone, each firm must incur an initial investment $I > 0$ before the inventor exerts effort to innovate. If two firms merge and the merged firm retain both inventors, the necessary initial investment is KI, where $K \leq 2$ measures the degree of economies of scale. If the merged firm fires one inventor, the initial investment is reduced to I.

For the merged firm, the expected profit when retaining both employees is:

$$\pi^{M*}(I) = -KI + (e^{M*})^2(1-2\beta)(v-1+(r-v)^+)M + 2e^{M*}(1-\beta)(1-v)M,$$

where e_i^{M*} is defined in equation (4).

If the firm keeps only one inventor, we know from Lemma 1 that the expected profit is:

$$\pi^{M'*}(I) = -I + \frac{(1-\beta)(1-v)(v+\beta(1-v))M^2}{k}.$$

Lemma 1 shows that $\pi^{M'*}(I) < \pi^{M*}(I)$ when $I = 0$. Comparing $\pi^{M'*}(I)$ and $\pi^{M*}(I)$ yields $\pi^{M'*}(I) \leq \pi^{M*}(I)$ if and only if

$$K \leq \frac{(e^{M*})^2(1-2\beta)(v-1+(r-v)^+)M + 2e^{M*}(1-\beta)(1-v)M - (1-\beta)(1-v)(v+\beta(1-v))M^2/k}{I} + 1 \equiv K^C$$

Given that we have $K \leq 2$, then if $K \leq \min\{K^C, 2\}$, the post-merger firm chooses to have two inventors. If $K > \min\{K^C, 2\}$, then the post-merger firm finds it optimal to scale down and retain only one inventor.

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[15]. 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 synergy, 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

[15]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.

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 synergy between the target and acquirer firms. This approach allows us to quantify the alignment of technological capabilities and identify synergies that may enhance post-merger innovation outcomes.

B.2. Merging Failed Mergers With the Census Data

Once the failed merger deals are identified in the SDC Platinum Database, we proceed with matching 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. We use the LBD data to identify mergers and acquisitions. Overall, we are able to match about 60% of target firms and 70% of acquirer firms 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.