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

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Abstract

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

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1 Introduction

Innovative firms are increasingly being acquired by incumbent firms rather than going public through IPOs (Cunningham et al., 2021; Ederer and Pellegrino, 2023), raising policy concerns about the effects of mergers and acquisitions (M&As) on innovation (Federico et al., 2020). A common motivation for M&As is the acquisition of skilled talent,[1] and recent research shows that such mergers can negatively affect workers by increasing firms' labor market power (Arnold, 2019; Berger et al., 2025). In this paper, we study how M&As influence innovation through changes in labor market power over innovative workers. We show theoretically and empirically that M&As strengthen firms' labor market power over inventors, thereby reducing their incentives to innovate and diminishing their productivity.

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 enrich it by incorporating innovation synergies and labor market competition. The firms either operate independently as stand-alone entities 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, in which case combining the innovations creates additional value. 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 inventors' effort when the level of product market competition is low and innovation synergy is small. This is because mergers reduce labor market competition: under the stand-alone structure, the two firms compete for inventors, and successful inventors capture more rents; when two firms merge, inventors expect to receive lower rents from their innovations and thus exert less effort 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. Higher innovation synergies and product market competition also attenuate the negative impact of mergers on innovation because synergies

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

increase total rents and inventor effort under the merged firm and a more competitive product market diminishes total rents and inventor effort under the stand-alone structure.

To empirically test these predictions, we use individual-level, longitudinal data from the U.S. Census Bureau to estimate how the impact of M&As on inventor outcomes depends on labor market power and other channels. The data offer two unique advantages. First, we are able to link patent inventors to survey, census, and administrative employee-employer information at the Census Bureau building on the linkages developed in Akcigit and Goldschlag (2023a). Second, the administrative data allow us to examine a comprehensive set of M&As, including acquisitions of smaller private firms that are not subject to antitrust review and not captured by standard databases like SDC Platinum. Our final sample consists of around 3,300 mergers between U.S. innovative firms over the period of 2005–2017. We define an inventor as an employee of the target or acquirer firm who has at least one patent in the five years preceding the merger. There are 21,500 unique inventors in the target firms and 109,000 unique inventors in the acquirer firms. An average inventor has 0.7 patents per year.

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

To test the labor market power channel, we compare the innovation and labor market trajectories of high-impact inventors, for whom the merger has a high predicted impact on labor market power, to those of low-impact inventors around M&As. The key identifying assumption is that, in the absence of mergers, the difference between high-impact inventors and their respective counterfactual inventors, and the difference between low-impact inventors and their respective counterfactual inventors, would have followed similar trends over time. We measure labor market power using labor market concentration following prior literature (e.g., Arnold, 2019), with two key modifications to account for the unique features of the inventor labor market. First, we use inventors' field of specialization instead of industry or occupation to define labor markets. Second, we use inventors' mobility patterns to flexibly define labor markets geographically instead of confining labor markets to a single local area. High-impact inventors are defined as inventors who have

an above-median labor market concentration before the merger and experience an above-median increase in labor market concentration due to the merger. The impact on labor market concentration varies by an inventor's field and location, such that a merger may significantly increase labor market power for some inventors while having little effect on others within the same firm.

We further examine the synergy and product market competition channels by comparing treated inventors in high-synergy (or high-product-market-competition) mergers with those in low-synergy (or low-product-market-competition) mergers. A merger has high potential innovation synergy if the pre-merger innovations of the two merging firms exhibit high complementarity and low substitutability. We measure product market competition using the industry concentration of the target or acquirer firm prior to the merger.

We assess three dimensions of inventor outcomes—patents, earnings, and job mobility—for both target and acquirer inventors. To our knowledge, these have never been systematically studied together in empirical work on M&As and innovation, and certainly not in a setting with rich administrative data. These outcomes are important to consider jointly because they provide a holistic picture of the impact of M&As on innovation and inventors and enable us to test the different channels.[2]

Consistent with our model predictions, we find a larger negative effect of mergers on inventor productivity when mergers increase firms' labor market power by more. High-impact inventors at target firms have 0.13 fewer patents per year following the merger compared to low-impact inventors, which is a 20% decline relative to the mean. High-impact inventors at acquirer firms file 0.10 fewer patents per year—15% less than the average—compared to low-impact inventors. Supporting our identifying assumption, the number of patents of high-impact and low-impact inventors exhibit similar trends before the merger, and the gap widens over time after the merger. The quality of patents by high-impact inventors also declines, as evidenced by a larger drop in high-citation patents relative to low-citation ones after mergers. Consistent with the synergy channel, we see an increase in inventor productivity for high-synergy mergers, which is concentrated mostly among target firm inventors. We also observe a larger decline in patent counts following mergers in high-concentration

[2]For example, a limitation of using patents to measure innovation is that they miss innovations that are not patented (e.g., scientific publications, trade secrets, or commercialization of innovation). Observing inventors' earnings helps address this concern because a higher level of non-patented innovations should be correlated with higher earnings.

industries, consistent with the product market competition channel.

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

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

We perform several additional tests to address the concern that unobserved shocks affecting high-impact inventors at target and acquirer firms may coincide with M&As.[3] First, we control for unobserved firm-level shocks by including firm fixed effects or firm-by-commuting-zone fixed effects and show that the results are robust when comparing high-impact inventors within firms and within firm-commuting-zone cells. Second, to control for unobserved field-specific shocks that are correlated with the concentration of innovation in a field, we construct an analogous measure of the merger's impact on concentration in the innovation market based on the number of patents. We find that accounting for the merger's impact on concentration in the innovation market does not alter the effect of labor market concentration for inventors. Third, we run a placebo test using failed mergers and do not see a similar effect on high-impact inventors. We also show that spinoffs—which reduce firms' labor market power and enhance inventors' incentives to innovate—

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

have the opposite effect on high-impact inventors compared to mergers (although the effects are not statistically significant due to the smaller sample size).

Our baseline results are robust to alternative samples, additional controls, alternative definitions of labor market concentration, and incorporating firm investment in R&D. We find similar results when matching treated inventors to counterfactual inventors three years before the merger, which allows us to include inventors who may have left the firm in anticipation of the merger. We also show that our results are robust to controlling for overlap in innovation and product markets between the merging firms. Allowing for firm investment in R&D can theoretically amplify the negative effect of labor market power, and we find empirically that high-impact mergers are associated with lower R&D investment compared to low-impact mergers. However, the decline in R&D investment is small and insignificant even among high-impact mergers, suggesting that lower productivity of high-impact inventors is not primarily driven by lower firm investment in R&D.

While mergers make inventors worse off, the impact on firm profits is ambiguous. On the one hand, firms benefit from increased labor market power, which allows them to extract more rents from successful innovations. On the other hand, lower inventor effort and productivity reduce total rents and firm profits. Lower separation rates of high-impact inventors partially offset the loss of innovation as firms retain more inventors and their innovations. Overall, we find that the impact on labor market concentration is not associated with post-merger changes in firm-level labor productivity or earnings per worker. Using the sample of publicly listed firms, we show that high-impact mergers do not differ in terms of merger premiums or short-term returns following the merger announcement, but have significantly lower returns months after the merger. In contrast, high-synergy mergers have higher premiums but do not have higher post-merger returns, suggesting that acquirer firms tend to overbid when there is high potential innovation synergy.

We show that the labor market channel is quantitatively important for the aggregate impact of M&As on innovation. Overall, mergers have an average negative and significant effect on the number of patents and earnings of inventors at both target and acquirer firms, suggesting that the negative effect due to increased labor market power dominates the positive effects from innovation synergy and reduced product market competition.

This paper makes two main contributions: first, we demonstrate that mergers lower inventors' productivity by weakening competition in the labor market; second, we provide systematic evidence

that labor market power is a key mechanism driving the negative impact of mergers on innovation. While antitrust authorities have expressed concerns about the potential negative effects of mergers on innovation (Federico et al., 2020),[4] previous work mostly focuses on firm-level investment in innovation and firms' incentives to innovate. This neglects the key role inventors play in driving innovation: for example, Bhaskarabhatla et al. (2021) finds that inventor fixed effects explain the largest part of variation in patenting, and labor costs account for over two thirds of R&D expenditure by US firms.[5] Our empirical evidence highlights the importance of considering labor market power and its impact on inventor incentives in the context of mergers and innovation.

We contribute to several branches of literature. Our paper is most closely related to the literature on how M&As affect innovation. Prior work has documented innovation synergies (Bena and Li, 2014; Li and Wang, 2023), outsourcing of R&D to target firms (Higgins and Rodriguez, 2006; Phillips and Zhdanov, 2013; Ma, 2020), and how mergers address hold-up problems in innovation investment (Bena et al., 2023). Several papers show that mergers have anti-competitive effects on innovation and reduce firms' incentives to invest in R&D (Ornaghi, 2009; Szücs, 2014; Federico et al., 2017; Cabral, 2018; Haucap et al., 2019). In a more extreme case, Cunningham et al. (2021) document that pharmaceutical firms engage in "killer" acquisitions to eliminate future competition. Our paper focuses on the supply side of innovation and provides empirical support for Fulghieri and Sevilir (2011), who first proposed that mergers reduce inventor incentives by lowering labor market competition. Our results are also in line with Seru (2014), who shows that target inventors have lower patenting productivity after M&As. In addition, our administrative data enable us to examine the effects of all mergers between innovative firms in the U.S. and expand beyond the typical focus on publicly listed firms.

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

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

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

major motivation for mergers and such mergers may be socially inefficient. Our results on inventor earnings are consistent with these results, and the inventor setting also allows us to examine changes in individual-level productivity around M&As.

We also contribute to the growing literature on labor market power. Recent papers have documented strong negative associations between labor market concentration and wages (Azar et al., 2022; Benmelech et al., 2022; Schubert et al., 2024). We develop a novel measure of labor market concentration for inventors based on technological fields. We show that M&As contribute to rising labor market power over high-skilled workers as documented in Seegmiller (2021), and the increased labor market power also depresses worker incentives and productivity. 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) can affect inventors' innovation outputs.

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

2 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 incorporating innovation synergy and labor market competition. All proofs and technical parameter

restrictions are in Appendix A.

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 firms 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, where $\delta \in [0, 1]$.[6] 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 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

[6] 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.

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 also 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 1. 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 inventor effort 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. Lower labor market competition diminishes inventors' outside options under the merger, therefore reducing their incentives and effort to innovate.[7]

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 the level of inventor effort, 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. On the other hand, merger may lead to lower inventor effort and reduce the total payoff from innovation. The following proposition shows that it is optimal for firms to merge when employee bargaining power β is sufficiently high.

Proposition 2. If $\beta \geq \beta_c$, the two firms obtain greater expected profits with the merger, where $\beta_c \in [0, 1]$ is defined in the Appendix.

When employee bargaining power is sufficiently high, employee incentives to exert effort are

[7] This is a key insight from Fulghieri and Sevilir (2011), and in our model we further allow for labor market competition from firms other than the merging firms and study how the effect depends on external labor market competition.

already strong even with weak outside options. Therefore, the two firms find it desirable to merge to enjoy the monopoly position in the product market and to extract greater rents from employee innovations.

More generally, firms may find it optimal not to merge if the ex-ante negative effect on inventor effort dominates the ex-post benefit of market power and synergy.[8] In Appendix A.3, we use a numerical exercise to show that when β is small, firms may find it desirable to remain as stand-alone firms. We also show that when firms have high labor market power, merger may benefit the firms but hurt the total surplus and overall welfare, because firms do not internalize the negative spillovers on inventors when considering whether to merge.

In this model, we focus on inventors' incentives to innovate and assume that inventor effort is the only input to innovation. In Appendix A.2, we consider the more general 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.

How does the merger affect inventors' job mobility? 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.[9] First, merger directly reduces inventor mobility by eliminating inventor movements between the two stand-alone firms. This effect is larger when inventors are concentrated in a small number of firms and have limited outside options. Second, since inventors who have successful innovations are more likely to be poached by other firms, merger reduces inventor mobility if it reduces inventors' effort and probability of success (and vice versa). This effect is also more negative when inventors have fewer outside options, in which case the merger has a more negative effect on inventor effort and productivity.

3 Data

To study the impact of M&As on inventors, we use firm- and worker-level data from the U.S. Census Bureau. The firm-level dataset is the Longitudinal Business Database (LBD). The dataset covers

[8] 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.

[9] In our model, inventors never move to the other firm under the stand-alone structure; after the two firms merge, an inventor moves his innovation to the external market when both inventors successfully innovate and $r < v$.

all non-farm establishments with paid employees in the U.S. from 1987 to 2021. An establishment is defined as a specific physical location where business operations occur. The data provide information on plant-level owner (firm), geographic location (state and county), industry (six-digit NAICS), employment, and payroll.

The worker-level dataset is the Longitudinal Employer Household Dynamics (LEHD). The LEHD data provide information on workers' employer, earnings, gender, race, and age. It is constructed using administrative records from the state unemployment insurance (UI) system and the associated ES-202 program. Worker earnings include salary and wage earnings as well as bonuses, stock options, profit distributions, the cash value of meals and lodging, tips, and other gratuities in most states and, in some states, employer contributions to certain deferred compensation plans such as 401(k) plans. We have access to LEHD worker-level data from 22 states and the District of Columbia, which covers about half of the U.S. population.[10] The LEHD earnings data are currently available from the 1980s through 2021 (the start date varies across states and ranges from 1985 to 2002). While we include earnings from all employers, we associate workers with their "dominant" employer (i.e. the employer for which the worker earns the highest income) in each year.

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).[11]

We use the U.S. Patent and Trademark Office (USPTO) data to identify the patents associated with each inventor. Our data cover all patents granted between 2000 and 2021. We use the application date to calculate the number of patents associated with each inventor in each year. In addition, we use the number of citations received by each patent to measure the quality of patents and patent technology classes to determine the technological fields of inventors.

Mergers and Acquisitions. We use the LBD to identify mergers and acquisitions. In the LBD data, when an establishment changes ownership, the establishment-level identifier remains unchanged, whereas the firm identifier changes. As a result, we are able to infer M&As by observing

[10]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.

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

when firm-level identifiers change (Maksimovic and Phillips, 2001; Arnold, 2019; Tate and Yang, 2023). To avoid spurious changes in firm identifiers unrelated to mergers, we only keep cases where two or more firm identifiers of establishments merge into one. For example, if establishment 1 has firm identifier A and establishment 2 has firm identifier B in a year, and they both have firm identifier A in the following year, we infer that the two establishments merge where firm A is the acquirer and firm B is the target. We drop cases where the new firm identifier did not exist before the merger, in which case we cannot identify the acquirer or target. We keep only full mergers, where all establishments of the target are acquired by the same acquirer.

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

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

4 Empirical Strategy

In this section, we describe our empirical strategy to test the model predictions in Section 2. First, we match each inventor in a target or acquirer firm to a "counterfactual" inventor in a firm without any M&A activities. Second, we use our inventor-firm matched data to measure labor market power and synergy from the merger. Finally, we estimate a dynamic difference-in-differences specification comparing the outcomes of treated inventors and control inventors over time to identify the impact of mergers on inventor outcomes.

4.1 Matching to Counterfactual Inventors

We construct the inventor sample as follows. We refer to an inventor-year observation as experiencing a year-t M&A event when (i) the worker has at least one patent within the recent five

years; (ii) the worker has positive earnings in year $t-1$, with earnings of at least \$2000 in all four quarters;[12] and (iii) the worker's dominant firm (the firm with the highest earnings) in year $t-1$ is either a target or an acquirer of a merger event between year $t-1$ and t.

We then match each such inventor-t observation to a "counterfactual" inventor-t observation that satisfies the following criteria: (i) the dominant firm in year $t-1$ did not experience any M&A activity within the (-5, +5) year window; (ii) the worker has at least one patent within the recent five years; (iii) the worker has earnings no less than \$2000 in all four quarters of year $t-1$; and (iv) the observation matches the treated inventor-year observation along the following five dimensions:

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

Matching on these various dimensions helps in identifying counterfactual inventors that would plausibly exhibit common trends to treated inventors in the absence of M&As. If multiple inventor-t observations satisfy all the criteria, we select the one with the most similar number of patents over the past five years as the counterfactual inventor.

We then construct a balanced panel of inventor outcomes for each treated inventor i and the matched counterfactual inventor i' from five years before to five years after the merger event.[13] 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 obser-

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

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

vations for acquirer firms from 3,300 M&A events between 2005 and 2017.[14] Figure 1 plots the number of M&As in each year. Table 1 reports summary statistics from this sample. As the table shows, treated inventors and counterfactual inventors have similar patenting activities and earnings as a result of our matching procedure. Appendix Figures A4 and A5 plots the distribution of inventors across industries and technological fields. For each inventor, we take the field with the most number of patents as the main technology field. We see that the inventors in our sample span across all industries, with the highest concentration in manufacturing and tech sectors ("Information" and "Professional Services"). The technology fields with the largest numbers of inventors are "Computing; Calculating or Counting (G06)" (16% of target inventors and 22% of acquirer inventors) and "Electric Communication Technique (H04)" (18% of target inventors and 15% of acquirer inventors).

4.2 Measuring Labor Market Power and Synergy

To measure labor market power, we use labor market concentration following the recent labor economics literature (Arnold, 2019; Benmelech et al., 2022; Schubert et al., 2024). Since we focus on inventors, we make two important deviations from the literature in defining labor market concentration. First, instead of using industry or occupation, we use inventors' fields of specialization to define labor markets for inventors. This is because 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). When inventors move, almost all of them (over 90%) move to another firm with at least one inventor working in the same field, even though they often switch occupations and industries. Second, we do not restrict to local labor markets when defining labor markets for inventors, because high-skilled workers like inventors are more mobile than the average worker (Moretti and Wilson, 2017; Amior, 2024) and we observe a lot of cross-commuting-zone and cross-state movements for inventors in our data. Instead, we use a geography-mobility-adjusted labor market concentration measure akin to the occupation-mobility-adjusted measure in Schubert et al. (2024) to define labor markets geographically based on empirical patterns of inventor mobility across regions.

Specifically, for an inventor in technology class m and commuting zone c, the mobility-adjusted

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

Herfindahl-Hirschman Index (HHI) is defined as:

$$HHI_{mc}^{MA} = \sum_{i=1}^{N} s_{imc}^2 = \sum_{i=1}^{N} \left(\frac{\sum_p n_{imp} \times 1(\pi_{c \to p}^m > x)}{\sum_p n_{mp} \times 1(\pi_{c \to p}^m > x)} \right)^2, \tag{5}$$

where s_{imc} is firm i's market share for technology class m and commuting zone c, and n_{imp} is the number of inventors whose main technology class is m in firm i in commuting zone p. Technology class m is measured at the 4-digit CPC subclass level and there are around 600 technology classes in total. The dummy $1(\pi_{c \to p}^m > x)$ equals one if the probability of moving from commuting zone c to p for inventors in technology class m is greater than some threshold x (e.g., 0 or 1%).[15] Intuitively, the labor market for inventors in technology class m and commuting zone p contains commuting zone c if the probability of moving from p to c for inventors in that field is sufficiently high. For example, if biotech inventors often move from Boston to the Bay Area, a merger between two Boston-area firms would have a smaller impact on the mobility-adjusted HHI because the biotech inventors in the Boston area still have a lot of outside options in the Bay Area. Note that this measure is asymmetric: commuting zone p may not be in the labor market for inventors in commuting zone c even when commuting zone c is in the labor market for inventors in commuting zone p.

We then calculate the predicted change in HHI due to the merger for inventors in technology class m in commuting zone c as:

$$\Delta HHI_{mc}^{MA} = 2 s_{amc} s_{tmc} = 2 \left(\frac{\sum_p n_{amp} \times 1(\pi_{c \to p}^m > x)}{\sum_p n_{mp} \times 1(\pi_{c \to p}^m > x)} \right) \left(\frac{\sum_p n_{tmp} \times 1(\pi_{c \to p}^m > x)}{\sum_p n_{mp} \times 1(\pi_{c \to p}^m > x)} \right), \tag{6}$$

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

We split our sample into high-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 therefore define high-impact inventors as those with an above-median initial level of HHI in the year before the merger and an above-median predicted change in HHI resulting

[15] We describe how we measure the commuting zone of each inventor in Appendix B.3. The baseline measure uses cutoff $x = 0$, and we consider alternative measures in Section 5.4.1.

from the merger.[16]

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

4.3 Empirical Specification

We use the sample of treated inventors and counterfactual inventors to estimate the impact of M&As using a difference-in-differences specification. In particular, let i denote a treated inventor in a target or acquirer firm and i' denote the matched counterfactual inventor. Let j denote the firm-event combination.[17] 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:

$$\Delta Y_{ii'js} = \alpha Post_{ijs} + \gamma Post_{ijs} \times HighImpact_{ij} + \mu Post_{ijs} \times HighSynergy_{ij} + X'_{ijs}\beta + \varepsilon_{ijs}, \quad (7)$$

where $Post_{ijs}$ equals one if inventor i experienced an M&A event (denoted by j) before year s, $HighImpact_{ij}$ is an indicator for high-impact inventor, and $HighSynergy_{ij}$ is an indicator for

[16] We calculate the median for the sample of target inventors and the sample of acquirer inventors separately.
[17] For a given event, firm refers to the firm identifier in year $t-1$.

high-synergy merger. The control variables X_{ijs} include an indicator for pre-merger periods,[18] the high-impact dummy $HighImpact_{ij}$, high-synergy dummy $HighSynergy_{ij}$, and the interactions between the pre-merger indicator and the high-impact and high-synergy dummies. We cluster standard errors at the firm-event level j. In this specification, γ reflects the differential impact of mergers on high-impact inventors relative to low-impact inventors, and μ reflects the differential impact of high-synergy mergers relative to low-synergy mergers. According to our model, γ should be negative and μ should be positive for inventor productivity and earnings.

We also consider a dynamic event study specification as follows:

$$\Delta Y_{ii'js} = \sum_{k\in -5,-4,-3,-2,0,1,2,3,4,5} \left(\gamma_k D^k_{ijs} \times HighImpact_{ij} + \mu_k D^k_{ijs} \times LowImpact_{ij}\right) + \epsilon_{ijs}, \quad (8)$$

where D^k_{ijs} is an indicator for inventor i having experienced the M&A event (denoted by j) k years in the past, and $LowImpact_{ij}$ is the complement of $HighImpact_{ij}$. The coefficients of interest, γ_k (and μ_k), provide the time path of the difference in outcomes between high-impact (and low-impact) inventors and their counterfactual inventors relative to the year before the merger event, which is normalized to zero.

5 Main Results

5.1 Effects on Inventor Productivity

The model in Section 2 predicts that mergers have a more negative effect on inventor effort, productivity, and earnings when the merger has a bigger impact on labor market power and inventors' outside options. We start by examining the effect of mergers on inventors' innovative productivity. Our main measure of inventor productivity is the number of patents applied for in a given year that are eventually granted. Table 2 presents the results. Column 1 shows that high-impact inventors employed by the target firm have 0.139 (standard error = 0.066) fewer patents per year than low-impact inventors employed by the target firm following mergers. Given that the average number of patents per year is 0.67 for target inventors, this represents a 21% decline in the number of patents.

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

In column 2, we additionally interact the post-merger dummy with whether the merger has high potential innovation synergy, whether the acquirer's patents and target's patents have similar texts, whether the target firm is in a high-concentration industry (using the Herfindahl-Hirschman Index based on firm sales at the 4-digit NAICS level), and whether the merger is horizontal (i.e., the acquirer and target firms are in the same industry). The impact of labor market concentration remains unchanged with the additional covariates: high-impact inventors experience a decline in the number of patents per year by 0.132 relative to low-impact inventors. Consistent with the model predictions, we find that mergers with greater innovation synergy are associated with increased patenting. Inventors also have fewer patents when the patents of the two merging firms have high text similarity, suggesting that the merged firm may consolidate similar and substitutable innovations to improve innovation efficiency (Li et al., 2023). We also find more negative effects when the firm is in a high-concentration industry, although the difference is not statistically significant. Finally, whether a merger is horizontal has little impact on the number of patents because firms that are close in product market space may be distant in the technology space (Bloom et al., 2013).

The next two columns of Table 2 look at the effects on acquirer inventors. The findings for acquirer inventors align with those for target inventors. High-impact inventors experience a decline in the number of patents per year by 0.088 to 0.102 (a 13–15% decline relative to the mean) following M&As compared to low-impact inventors. High-synergy inventors at acquirer firms have more patents, but the difference is not statistically significant. Consistent with the model prediction, we see a larger decline in the number of patents after the merger if the acquirer is in a high-concentration industry.

To assess the relative importance of labor market competition, synergy, and product market competition in influencing inventors' productivity following mergers and understand the interactions between these channels, we split all inventors into eight groups by whether the merger has a high or low impact on labor market concentration for a given inventor, whether the merger has high or low innovation synergy, and whether the acquirer or target firm is in a high-HHI or low-HHI industry. Figure 2 plots the effects of mergers on the number of patents separately for each group. For target inventors in Panel (a), the two groups with negative and significant effects both have a high impact on labor market concentration and low innovation synergies. The four groups with high innovation synergies exhibit higher patenting rates following mergers, but none of the positive

effects are statistically significant. This suggests that the synergy partially offsets the productivity loss due to increased labor market power, but is not sufficient to have an overall positive impact on patenting even in high-synergy mergers. Panel (b) shows that acquirer inventors also experience the largest declines in the number of patents when mergers have a high impact on labor market concentration. However, acquirer inventors benefit little from synergies and the overall effects are close to zero even for high-synergy mergers.

We next look at the dynamic effects of mergers on inventor productivity using the event study specification in equation 8. Panels (a) and (b) of Figure 3 plot the effects on the number of patents by high-impact and low-impact inventors in target and acquirer firms respectively. In both target and acquirer firms, high-impact and low-impact inventors follow similar trends prior to the merger. However, their trends diverge after the merger: for high-impact inventors, there is a large and significant drop in productivity, whereas the drop in productivity is much smaller and statistically insignificant for low-impact inventors. The gap widens over time, since there is a lag between the time when an inventor exerts effort and the time of filing a patent.

How does the quality of patents change following mergers? To measure patent quality, we consider the number of forward citations normalized by patent technology class and grant year. We define high-citation patents as those with above-median citations in a year, and low-citation patents as those with below-median citations. Table 3 shows the effects of mergers on the number of high-citation and low-citation patents. For high-impact inventors in target firms, the number of high-citation patents decreases by 0.071 (22% of the mean) and the number of low-citation patents decreases by 0.061 (18% of the mean). For high-impact inventors in acquirer firms, the number of high-citation patents decreases by 0.074 (22% of the mean) and the number of low-citation patents decreases by 0.061 (8% of the mean). These results indicate that mergers with a high impact on labor market concentration reduce valuable and influential innovation in both target and acquirer firms. We also consider originality and generality (defined in Appendix B.4) as alternative measures of patent quality in Appendix Tables A1 and A2 and find that high-impact inventors experience larger declines in low-originality and low-generality patents.

5.2 Effects on Earnings and Job Separations

We next explore the effects of M&As on inventors' annual earnings in Table 4. When all covariates are included, high-impact inventors at target firms have 3.8% (standard error = 1.8%) lower earnings than low-impact inventors, and high-impact inventors at acquirer firms have 3.2% (standard error = 1.3%) lower earnings. Therefore, inventors get less reward from their innovations when mergers increase the labor market concentration. The table also shows that high-synergy inventors have lower earnings following mergers despite having higher productivity. This is likely because most of the surplus from higher innovation synergy is captured by the shareholders of target firms, which we document later.

Panels (c) and (d) of Figure 3 plot the earnings of high-impact and low-impact inventors relative to counterfactual inventors over time. There is a temporary jump in the earnings of target inventors in the first year following mergers, which is due to target inventors realizing gains from their equity holdings.[19] In both target and acquirer firms, high-impact inventors suffer much larger earnings losses than low-impact inventors. For example, in target firms, high-impact inventors have 9.6% lower earnings five years after the merger, compared to 3.5% lower earnings for low-impact inventors; in acquirer firms, high-impact inventors have 6.7% lower earnings five years after the merger, compared to 1.8% lower earnings for low-impact inventors.

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

Table 5 looks at the effects on separation rates of inventors. We define the separation rate as whether the inventor is no longer employed by the dominant employer in year -1.[20] Therefore, the separation rate is cumulative and is set to one once the inventor leaves the firm and joins another

[19] 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.

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

firm. We find that high-impact inventors are less likely to move to other firms after the merger: their separation rates decline by 6.9% and 3.8% more than those of low-impact inventors in target and acquirer firms, respectively, reflecting a greater reduction in outside options for high-impact inventors. Panels (e) and (f) of Figure 3 show that high-impact inventors have lower separation rates following mergers in both target and acquirer firms. In target firms, low-impact inventors are more likely to leave the firm than counterfactual inventors following mergers. This may be due to a poor fit (e.g., culture clash) between the target inventors and the acquirer firm (Kim, 2024),[21] but this effect is dominated by the negative effect of labor market power for high-impact inventors. These results imply that an additional benefit of merger for the firms is that it allows them to retain more inventors, as we discuss later.

5.3 Heterogeneous Effects

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

Appendix Table A4 explores heterogeneous effects by ex-ante firm characteristics. For target firm inventors, the effects are generally stronger for older and larger target firms (or younger and smaller acquirer firms), in which case the target and acquirer are more comparable and would compete more fiercely for the same talent prior to the merger. We also compare public and private target and acquirer firms. The effects are larger when the target firm is public and smaller when the acquirer is public, but the differences are not statistically significant. This suggests that our findings apply to the sample of publicly listed firms that has been extensively studied in the previous literature.

[21] Some previous studies also document higher departure rates of target firm employees following M&As, especially among key employees like executives (Martin and Mcconnell, 1991; Lagaras, 2019).

We explore the distribution of high-impact inventors by technological fields in Appendix Figure A6. Over half of the high-impact inventors are concentrated in three 3-digit CPC classes that are common in the tech sector: "Computing; Calculating or Counting (G06)," "Information Storage (G11)," and "Electric Communication Technique (H04)." This suggests that mergers tend to have large negative effects on patenting in the tech sector due to the high concentration of inventors.

5.4 Robustness and Additional Results

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

5.4.1 Alternative Measures of Labor Market Concentration

We consider four alternative measures of labor market concentration in Appendix Table A5. First, we use the coarser 3-digit CPC code to measure technology classes in Panel A. Second, we use a higher cutoff of 1% to define geographical markets so that commuting zone p is in the same labor market as commuting zone c for an inventor only if the probability of inventors in that inventor's technology class moving from c to p exceeds 1%. The results are shown in Panel B. Third, in Panel C, we count the number of inventors with *any* patent in technology class m when calculating n_{imp} and n_{mp} in equation 5. Finally, we use a weighted average of HHI and change in HHI across all technology classes to define high-impact inventors in Panel D. Specifically, for inventors with patents in multiple technology classes, we define $HHI_i^{MA} = \sum_m s_{im} HHI_{mc}^{MA}$ and $\Delta HHI_i^{MA} = \sum_m s_{im} \Delta HHI_{mc}^{MA}$, where s_{im} is the share of inventor i's patents in technology class m during the five years before the merger. Across these measures, we find that high-impact inventors have lower patents, earnings, and separation rates following mergers, with similar magnitudes to the baseline estimates.

5.4.2 Confounding Factors and Threats to Validity

Our empirical strategy compares treated inventors to matched counterfactual inventors, and the identifying assumption is that treated and counterfactual inventors follow parallel trends in patenting, earnings, and separation rates absent the merger. Supporting this assumption, we find no pre-trends in patenting or earnings prior to the merger in the event study analysis. However, it

is possible that mergers coincide with other unobserved shocks to the firm, leading to a classic omitted variable bias. Since we find differential effects for high-impact and low-impact inventors, and most of the effects are symmetrical across target and acquirer firms, any unobserved shocks need to affect high-impact inventors and not low-impact inventors at both target and acquirer firms to explain our results.[22] Below, we discuss some additional tests to alleviate this concern.

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

Controlling for Innovation Concentration. A related concern is that high-impact inventors may be in technology fields with unobserved negative shocks to productivity. For example, firms may wish to consolidate their R&D efforts through mergers in declining technological fields. The lack of pre-trends mitigates this concern, and we find in unreported analysis that the effects are stronger in technological fields with rising innovations rather than fields with declining innovations.

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

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

Table 7 shows that impact on concentration in the innovation market is not significantly associated with larger declines in patenting or earnings following mergers. In addition, controlling for impact on innovation concentration has little impact on the effect of impact on inventors' labor market concentration. These findings reinforce that our results are unlikely to be explained by high-impact inventors being in fields with declining productivity and consolidation between firms at the same time. Furthermore, these results suggest that our documented effects are specific to increasing labor market concentration for inventors and not merely driven by higher concentration in the innovation market.[23]

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

Table 8 shows the effects of failed mergers using the same specification as Table 2. We find

[23]Higher concentration in the innovation market can reduce firm investment in R&D and amplify the effects, as we will discuss later. We also see that when the two merging firms are directly competing in innovation and have highly similar patents, target firm inventors reduce their patenting after the merger to avoid competition. However, this channel is tangential to the labor market power channel as shown in previous sections.

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

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

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

Matching Three Years Before the Merger. Another threat to the validity of our results is that inventors may anticipate the upcoming merger and leave the target or acquirer firm before the merger occurs. This would bias our results because our analysis focuses on inventors in the merging

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

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

5.5 Decomposition Between Job-Movers and Job-Stayers

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

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:

$$y_t - y_c = \underbrace{(y_t^m - y_c^m)\delta_c}_{\text{Movers}} + \underbrace{(y_t^s - y_c^s)(1-\delta_c)}_{\text{Stayers}} + \underbrace{(y_t^s - y_t^m)(\delta_c - \delta_t)}_{\text{Separation rate}} \tag{9}$$

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

Given estimates of $\{y_t^s, y_c^s, y_t^m, y_c^m, \delta_t, \delta_m\}$, equation 9 apportions the observed difference in average outcome between treated and counterfactual inventors into three components: the difference in the average outcome of job-movers scaled by the separation rate; the difference in the average outcome of job-stayers scaled by the complement of the separation rate; and the difference in the separation rate scaled by the difference between the outcomes of the movers and the stayers. We then decompose the dependent variable in equation 8 into the three components for high-impact and low-impact inventors respectively.[26]

Figure 4 summarizes the results from the decomposition. For each period, we plot two bars indicating the effects on high-impact and low-impact inventors (compared to counterfactual inventors) respectively, and we decompose each bar into the three components in equation 9. Panel A shows that for target inventors, the difference between stayers accounts for almost all of the decline in patenting for high-impact inventors. Panel B shows that for acquirer inventors, stayers and movers both contribute to high-impact inventors' larger decline in patenting, with stayers explaining a larger part than movers. On the other hand, the lower separation rate of high-impact acquirer inventors contributes to higher productivity because stayers tend to patent more than movers (i.e., $(y_t^s - y_t^m)$ in equation 9 is positive). Panel C and Panel D depict similar patterns for earnings.

The results from this decomposition indicate that the decrease in patenting and earnings among high-impact inventors is primarily attributed to the lower earnings and patenting of high-impact stayers compared to low-impact stayers, consistent with lower incentives and effort levels for inventors staying at the merging firms.[27] While inventors can mitigate some of the negative effects by moving to other firms, we also see fewer patents and lower earnings for high-impact movers at acquirer firms. This may be because it's harder for movers to find the best match with fewer outside options, or that the lower incentives reduce human capital accumulation of the inventors.

[26] For each year, we calculate the separation rates δ_t and δ_c as the fraction of treated and counterfactual inventors who are no longer employed by the original firm. We then calculate each component of equation 9 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 8 to estimate the effects attributed to movers.

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

5.6 Average Effect of M&As on Inventors

In this section, we explore the average effect of M&As on inventors. As shown in the model in Section 2, higher labor market power depresses innovation, whereas synergies and reduced product market competition lead to more innovation. Therefore, the overall impact of M&As on inventor effort and earnings is theoretically ambiguous and depends on the relative strengths of the three channels (and other channels outside of our model).

To measure the average effect of M&As, we estimate the following event study specification:

$$\Delta Y_{ii'js} = \sum_{k \in -5,-4,-3,-2,0,1,2,3,4,5} \beta_k D^k_{ijs} + \varepsilon_{ijs}, \tag{10}$$

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

Figure 5 plots the coefficients β_k, which describe the average difference in outcomes between treated and matched counterfactual inventors relative to the year before the merger event. In all panels, the pre-trends are flat before the merger event, corroborating the parallel trends assumption. Five years after the merger, target inventors have 0.085 fewer patents per year (a 13% decline relative to the mean) and 5.2% lower earnings, whereas acquirer inventors have 0.080 fewer patents per year (a 12% decline relative to the mean) and 2.4% lower earnings. Appendix Table A8 shows the average effect across all post-merger periods. On average, mergers have a negative and statistically significant effect on the patenting and earnings outcomes of both target and acquirer inventors, as well as on the separation rates of inventors at acquirer firms. The average effect on target inventors' separation rates is near zero due to other channels causing higher separation rates of target inventors (e.g. cultural misfit). Although other channels may contribute to the negative effects of mergers on innovation, the negative average effect of mergers on patenting and earnings—together with the disproportionate impact on high-impact inventors shown in Figure 2—suggests that the labor market power channel plays a quantitatively important role in shaping the aggregate effects of mergers on innovation.

6 Discussion

In this section, we first explore the interaction between firm investment and the labor market power channel. We then examine how the labor market power channel affects firm profits and post-merger performance, and discuss broader implications of our results for welfare.

6.1 Firm Investment

In our model, we assume that inventor effort is the only input to innovation. In Appendix A.2, we consider a more general setting in which firms also need to invest in order to innovate. We show that when economies of scale are limited, the merged firm finds it optimal to fire one inventor to cut duplicate costs, which further amplifies the negative effect on innovation.

More generally, mergers can allow firms to internalize business-stealing effects, which reduces firms' demand for innovation when the target and acquirer firms were competing neck-to-neck prior to the merger (Aghion et al., 2005; Federico et al., 2017, 2020). If firm investment and inventor effort are complements, a reduction in firm investment can lead to a reduction in inventors' patenting productivity. Conversely, mergers can enable firms to internalize knowledge spillovers, thereby increasing the private returns to innovation and strengthening their incentives to innovate. Arora et al. (2021) show that firms produce more innovation when they can capture more of the spillovers it creates and underinvest in innovation when it is used by their rivals. Dix and Lensman (2025) show that the positive market expansion externality, which reduces investment by stand-alone firms when their innovations are complementary, dominates the negative business stealing externality in the pharmaceutical sector.

We empirically examine how firm investment interacts with the labor market power channel by estimating the event study specification 8 with firm-level R&D investment (scaled by lagged total assets) as the dependent variable. Since information on R&D is only available for public firms, this analysis uses the publicly listed firm sample. We focus on changes in R&D investment of the merged firm after the merger because most of the target firms are private and we do not observe the total R&D investment of the combined firm before the merger. In addition, since R&D investment is measured at the firm level, we can only exploit across-firm variation and not within-firm variation in impact on labor market concentration for this analysis.

Appendix Figure A7 presents the results. First, we see a larger decline in firm-level R&D investment for high-impact inventors, indicating that higher labor market concentration is also associated with an overall decline in firm investment in innovation. Since the majority of R&D investment is wages paid to R&D workers, part of the decline in R&D following mergers can be attributed to lower earnings of high-impact inventors. Second, the average change in R&D investment following mergers is almost zero, and even for high-impact mergers, the decrease in R&D is small (less than 1% of assets) and statistically insignificant. This suggests that the lower productivity of high-impact inventors is unlikely to be primarily driven by lower R&D investment by the combined firm.[28]

6.2 Impact on Firm Profits

The labor market power channel predicts that mergers have two opposing effects on firm profits: firms can extract greater surplus from innovation, increasing profits, but lower inventor productivity reduces profitability. Firms would choose to merge if the positive effect from rent extraction is larger than the negative effect from lower productivity. We find evidence supporting both effects—inventors have fewer patents and earn lower earnings, and both effects are stronger for high-impact inventors.

Our results imply two additional potential effects on firm profits. First, we show that the merged firm has higher retention rates of high-impact inventors, which enables the firm to recoup more innovation output from its inventors. Appendix Table A9 shows that the decrease in the number of patents by high-impact inventors belonging to the merged firm is smaller than the decrease in the total number of patents by high-impact inventors and is statistically insignificant. Specifically, the effects on the number of patents are 40% smaller for target inventors (column 2) and 55% smaller for acquirer inventors (column 4) than the effects in Table 2. This suggests that higher retention rates help mitigate the negative effect on firm innovation due to lower inventor productivity.

Second, the labor market power channel may also apply to other high-skilled labor beyond inventors and reduce worker incentives and productivity more broadly. Appendix Figure A8 shows

[28] Consistent with this interpretation, we also show in earlier sections that high-impact inventors exhibit lower productivity even within the same firm. Moreover, our results remain robust when controlling for factors related to the business-stealing effect, including changes in innovation market concentration, text similarity between target and acquirer patents, and product market overlap between merging firms.

that there is no decline in labor productivity for both high-impact and low-impact mergers. Appendix Figure A9 shows that the declines in earnings of other workers are much smaller than those for inventors, and there is no significant difference between high-impact and low-impact mergers. These results suggest that our documented effects on incentives and productivity are specific to inventors in our sample of mergers.[29]

Next, we explore the effects of labor market power and synergy on firm profits by looking at merger premiums and returns in Table 9. We match the publicly listed target and acquirer firms to the SDC Platinum data to get merger premiums (defined as the ratio of offer price to target stock price) and acquirer firms' post-merger returns. Column 1 shows that acquirers pay 18% more for target firms with high potential innovation synergies, indicating that synergies are highly valued by the bidder. In contrast, acquirers pay lower prices for mergers with high impacts on labor market concentration, and the difference is not statistically significant.[30] Columns 2 to 6 show that post-merger returns are slightly lower for high-synergy mergers throughout the post-merger period, suggesting that acquirer firms overpay for synergies and most of the surplus from innovation synergies is captured by the target's shareholders. On the other hand, a higher impact on labor market concentration does not correlate with short-term returns immediately after the merger, but strongly predicts lower returns one to three months after the merger. This implies that the negative effect of high-impact mergers on firm innovation is initially underestimated by the acquirer and the market.

6.3 Welfare Implications

How do mergers affect overall welfare? Our simple theory from Section 2 sheds light on this question. The theory implies social costs as well as benefits from M&As. By reducing ex-ante inventor effort, M&As reduce the innovation output in the economy, which could harm economic growth and consumer surplus. By creating innovation synergies and economies of scale (in the

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

[30] Both the positive effect from rent extraction and negative effect from lower inventor productivity are stronger for high-impact mergers, so the effect of labor market concentration impact on post-merger firm profits is ambiguous. We illustrate this non-monotonic relationship in the numerical exercise in Appendix A.3.

case with firm investment), M&As can potentially improve innovation efficiency and increase total surplus from innovation. The numerical exercise in Appendix A.3 illustrates that mergers can occur even if they harm overall welfare because firms do not internalize the negative impact on inventor payoffs when making merger decisions. Whether M&As improve or reduce overall welfare depends on the magnitudes of these effects 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 competition in the product market and innovation market. As a result, a full welfare analysis is beyond the scope of this paper, but two points merit discussion.

First, M&As have a long-lasting negative impact on inventors' careers. The decline in productivity and earnings does not revert after five years, and inventors have lower productivity and earnings even after they move to other firms. The most productive inventors experience the largest losses. Furthermore, lower rewards and reduced exposure to successful peers may affect career choices and discourage 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, the prospect of exit through acquisition by incumbent firms may affect startup entry and ex-ante firm investment in innovation (Phillips and Zhdanov, 2013; Kamepalli et al., 2020). Our results suggest that firms with inventors in highly-concentrated labor markets can be attractive acquisition targets because it allows the acquiring firms to pay inventors less and have lower inventor turnover. In our model, the amount of firm investment is fixed and there is no firm entry. However, it is possible that M&As may have a countervailing positive effect on welfare by increasing entrepreneurial entry.

7 Conclusion

This paper examines how mergers and acquisitions affect 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.

Our results are relevant for policy. They point to a quantitatively important negative effect of mergers on innovation due to higher labor market concentration for inventors. However, this channel has been overlooked by antitrust authorities until recently.[31] Our evidence suggests that labor market power with respect to inventors should be an important consideration when evaluating mergers between innovative firms.

More generally, the detrimental effects of labor market power on the incentives and productivity of innovative workers may extend to settings beyond mergers. Many firms use non-compete and anti-poaching agreements as well as long-term equity incentives to restrict mobility of their most talented workers. Recently, some firms have poached top talent from startup firms without mergers to bypass antitrust scrutiny.[32] Understanding the interaction between labor market frictions, firm strategies, and innovation represents a fruitful area for future research.

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

[32] See examples from Microsoft and Amazon.

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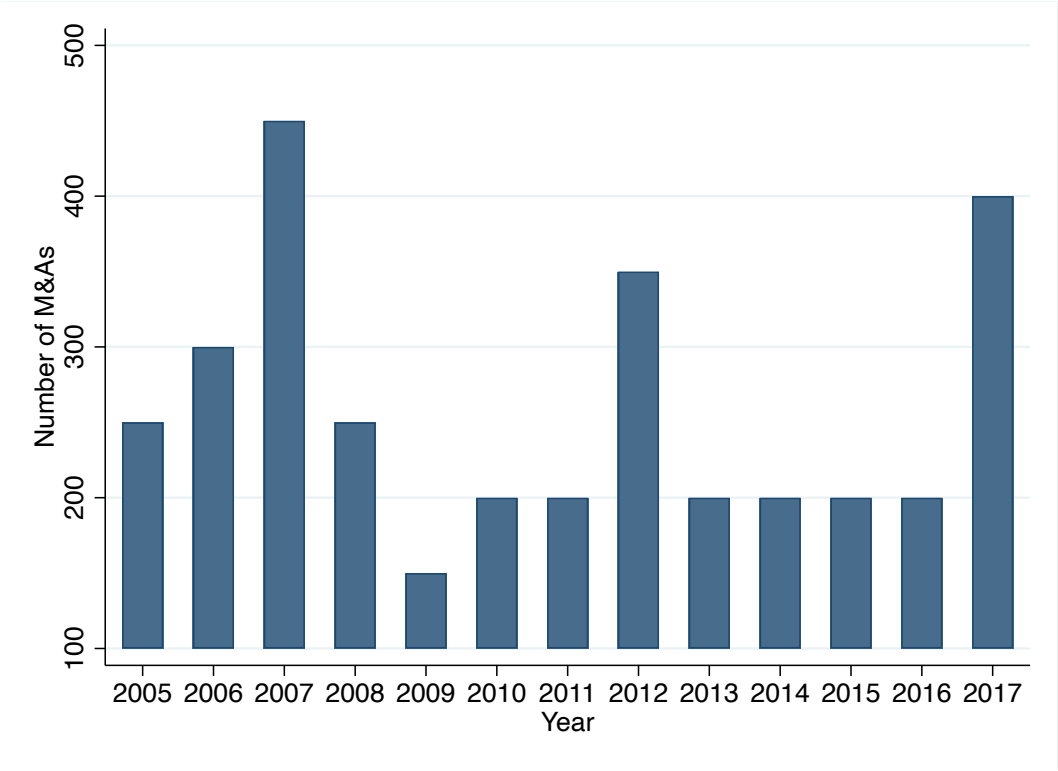
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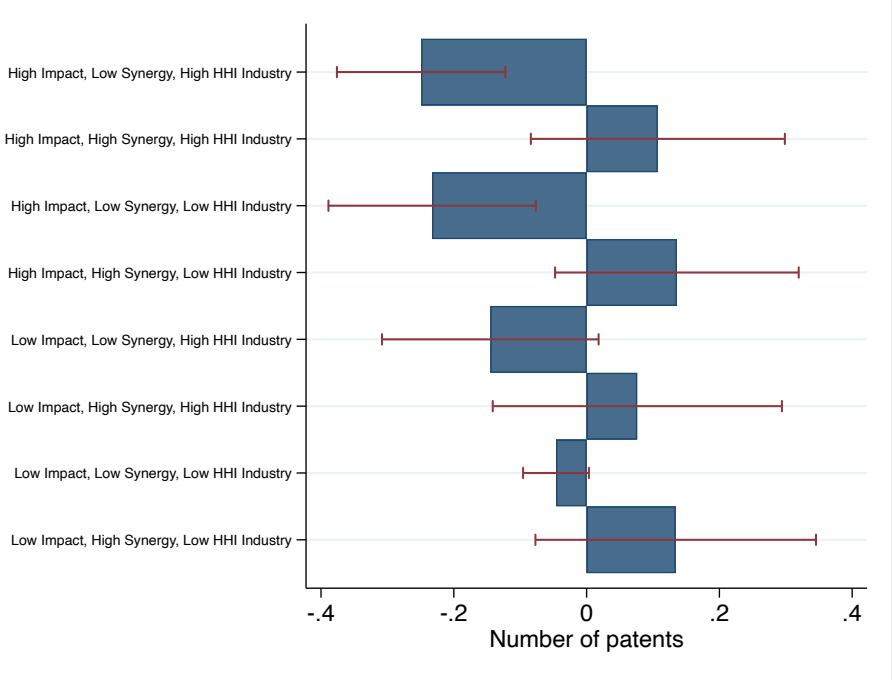
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Figure 1: Number of M&As by Year

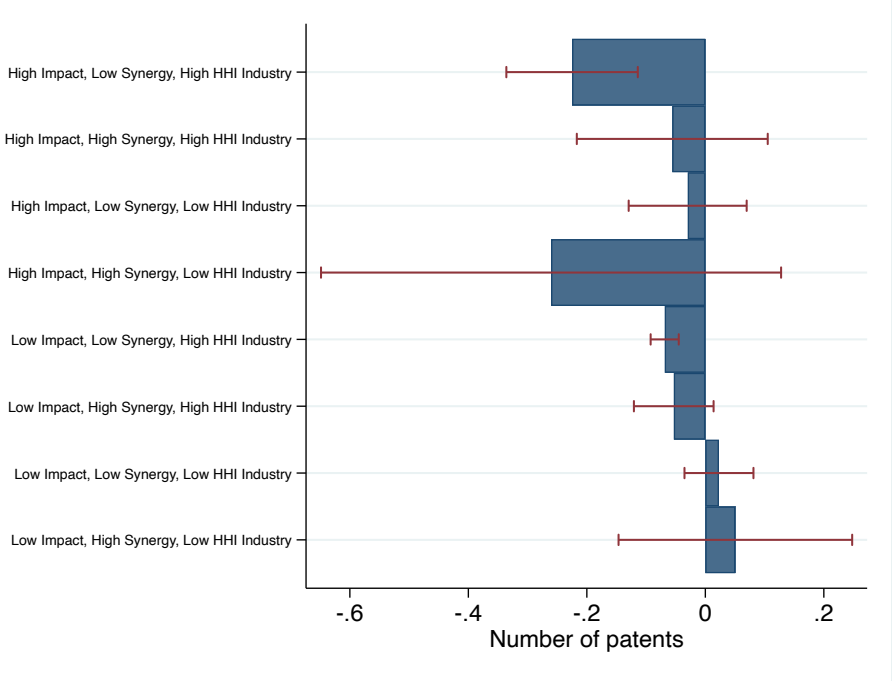


This figure plots the number of M&As in the U.S. each year between 2005 and 2017 in which the target firm has at least one active inventor. We define an inventor as an employee with at least one patent in the five years preceding the merger. The number of observations is rounded in accordance with the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

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



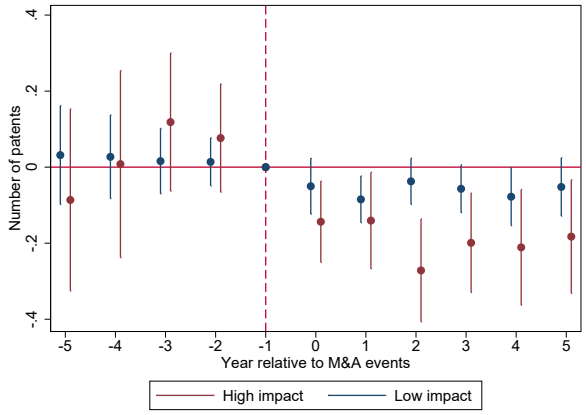
(a) Target Inventors



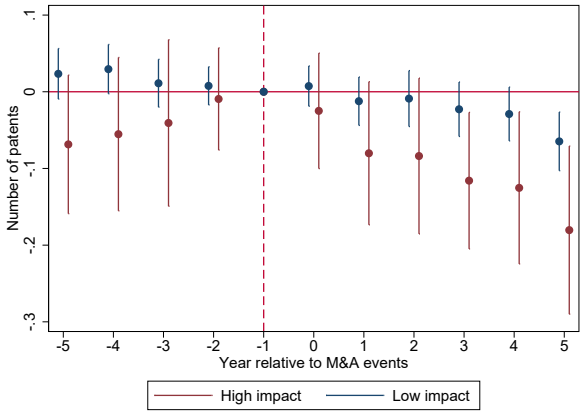
(b) Acquirer Inventors

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

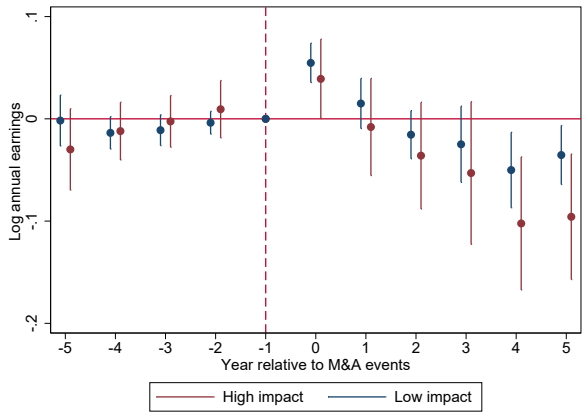
Figure 3: Changes in Inventor Outcomes around M&As for High-Impact and Low-Impact Inventors



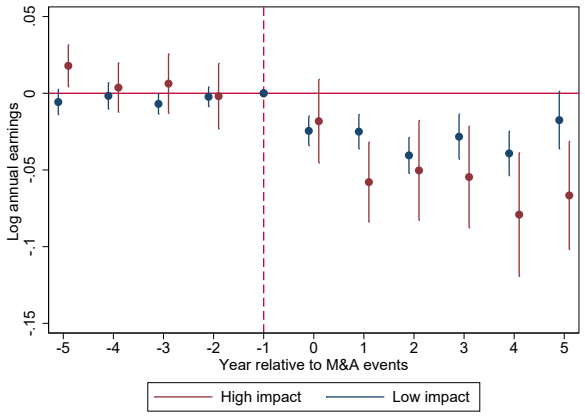
(a) Number of Patents, Target Inventors



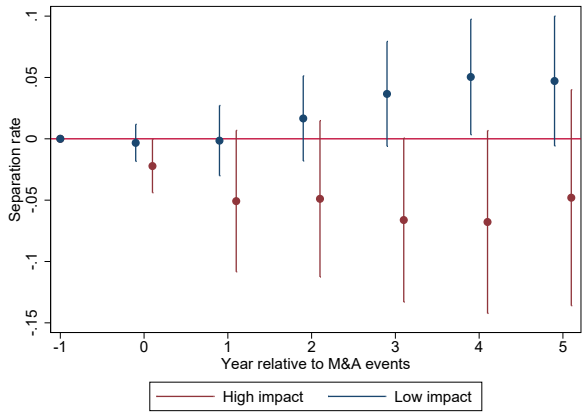
(b) Number of Patents, Acquirer Inventors



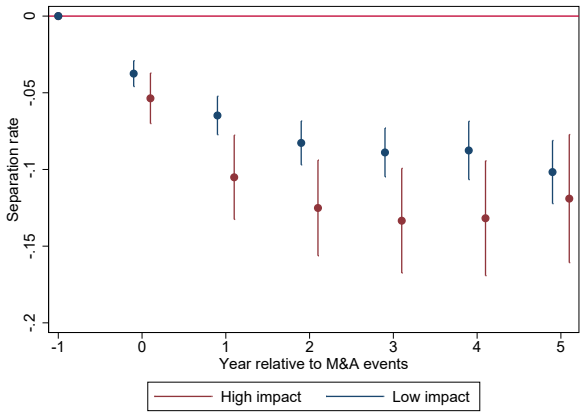
(c) Log Annual Earnings, Target Inventors



(d) Log Annual Earnings, Acquirer Inventors



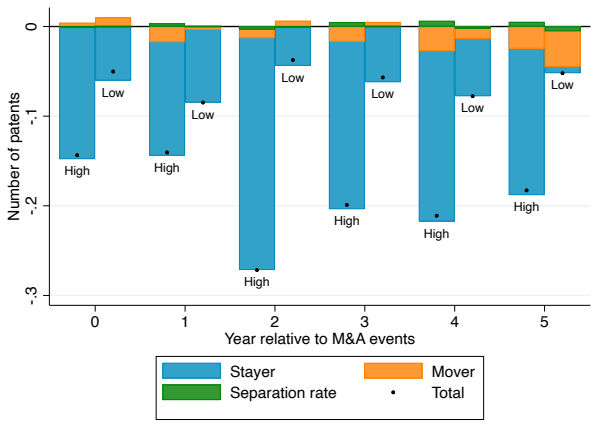
(e) Separation Rate, Target Inventors



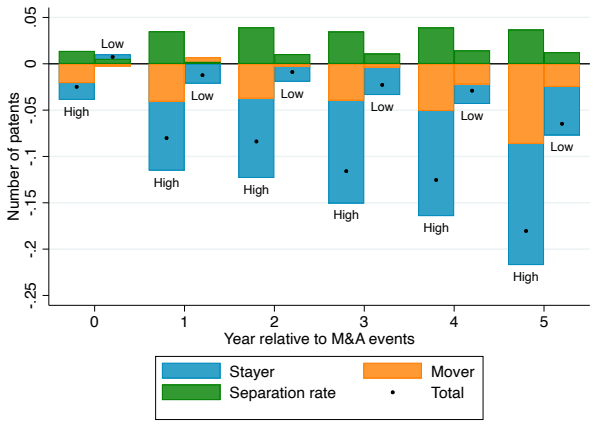
(f) Separation Rate, Acquirer Inventors

This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on inventor outcomes by high-impact and low-impact inventors based on equation 8. Panels (a), (c), and (e) show the estimates for target inventors, and Panels (b), (d), and (f) show the estimates for acquirer inventors. The dependent variables are the number of patents in Panels (a) and (b), log annual earnings in Panels (c) and (d), and separation rate in Panels (e) and (f).

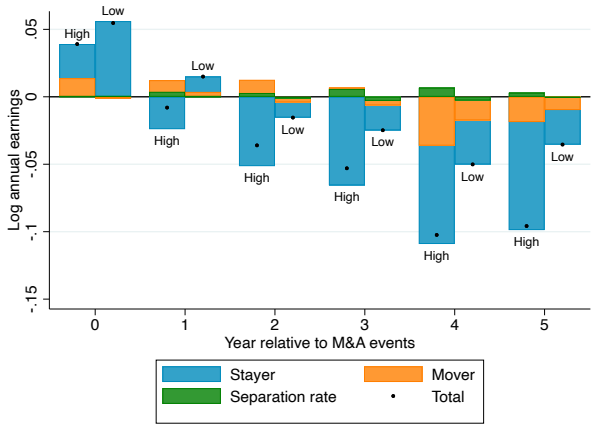
Figure 4: Decomposition of the Changes in Inventor Outcomes around M&As Between Stayers and Movers



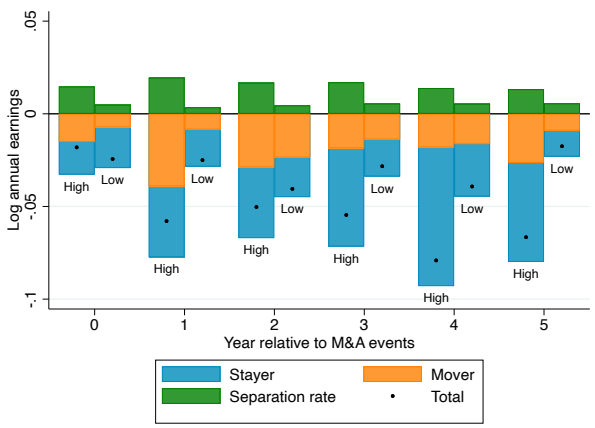
(a) Number of Patents, Target Inventors



(b) Number of Patents, Acquirer Inventors



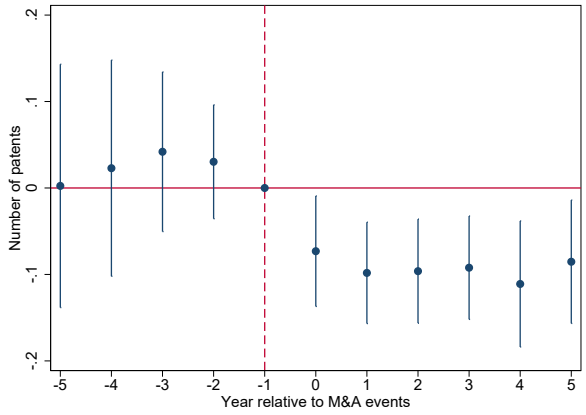
(c) Log Annual Earnings, Target Inventors



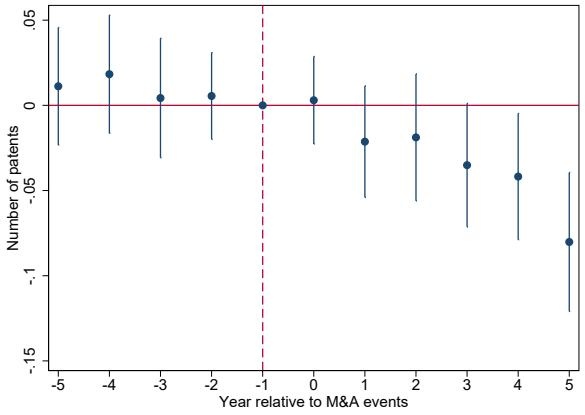
(d) Log Annual Earnings, Acquirer Inventors

This figure plots the decomposition of changes in inventor outcomes around M&As based on equation 9. For each post-merger period, two bars are shown representing the changes for high-impact and low-impact inventors (relative to counterfactual inventors) indicating. Each bar is further decomposed into three components: changes of stayers, changes of movers, and changes due to differences in separation rates. The black dots represent the sum of these three components. Panels (a) and (c) show the estimates for target inventors, and Panels (b) and (d) show the estimates for acquirer inventors. The dependent variables are the number of patents in Panels (a) and (b) and log annual earnings in Panels (c) and (d).

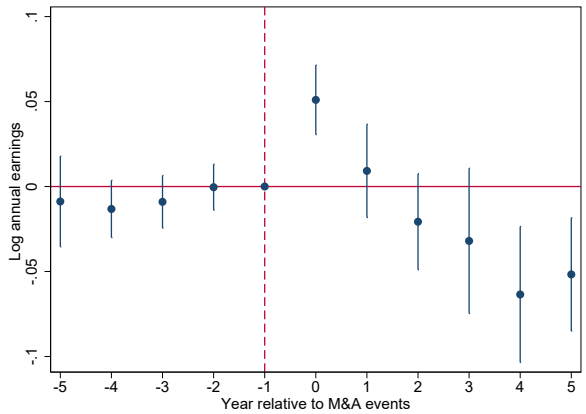
Figure 5: Average Changes in Inventor Outcomes around M&As



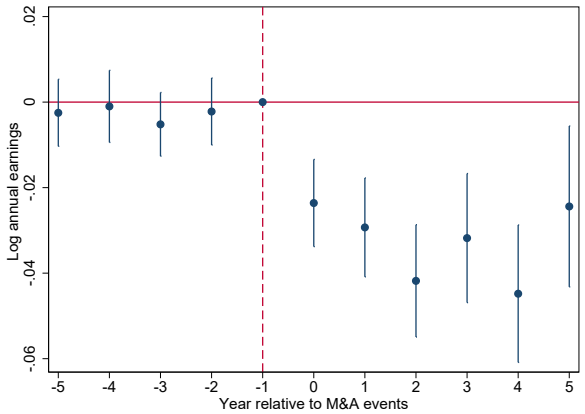
(a) Number of Patents, Target Inventors



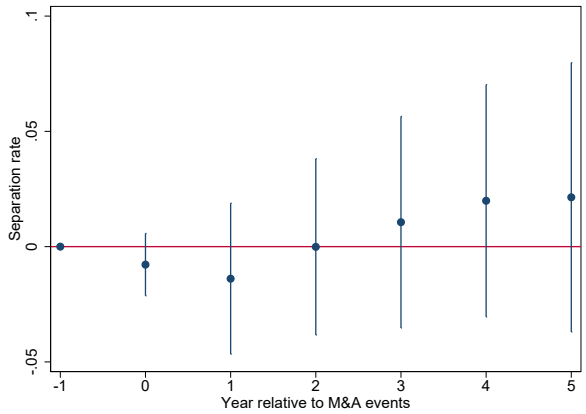
(b) Number of Patents, Acquirer Inventors



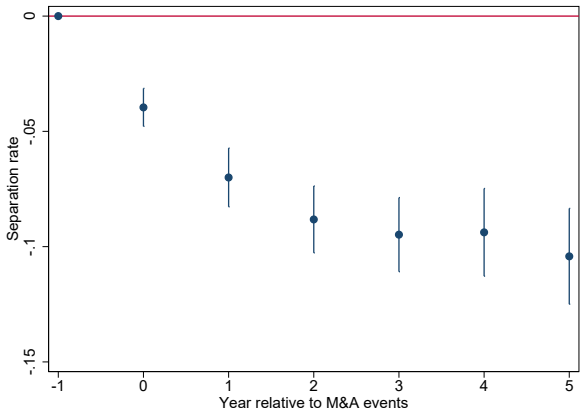
(c) Log Annual Earnings, Target Inventors



(d) Log Annual Earnings, Acquirer Inventors



(e) Separation Rate, Target Inventors



(f) Separation Rate, Acquirer Inventors

This figure plots event-study estimates and 95% confidence intervals for the average effect of M&As on inventor outcomes based on equation 10. Panels (a), (c), and (e) show the estimates for target inventors, and Panels (b), (d), and (f) show the estimates for acquirer inventors. The dependent variables are the number of patents in Panels (a) and (b), log annual earnings in Panels (c) and (d), and separation rate in Panels (e) and (f).

Table 1: Summary Statistics of Inventors

Panel A: Target Inventors

		Treated Inventors		Control Inventors	
	N	Mean	Std Dev	Mean	Std Dev
Age	160,000	45.52	9.002	45.61	9.080
Log Annual Earnings	160,000	12.00	0.7051	12.00	0.7034
Annual Earnings	160,000	251,400	1,909,000	243,000	1,311,000
Separation Rate	96,000	0.1889	0.3914	0.1870	0.3899
Number of Patents	160,000	0.6722	1.835	0.6436	1.492
Number of High-Citation Patents	160,000	0.3298	1.084	0.3392	0.992
Number of Low-Citation Patents	160,000	0.3423	1.097	0.3044	0.8408

Panel B: Acquirer Inventors

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

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

Table 2: Changes in the Number of Patents around M&As

	Target Inventors		Acquirer Inventors	
	Number of Patents			
	(1)	(2)	(3)	(4)
Post	-0.0623**	-0.0195	-0.0245	0.0135
	(0.0290)	(0.0355)	(0.0151)	(0.0343)
Post × High Impact	-0.1386**	-0.1321**	-0.0880**	-0.1024***
	(0.0661)	(0.0632)	(0.0381)	(0.0363)
Post × High Synergy		0.1919***		0.0354
		(0.0739)		(0.0509)
Post × High Text Similarity		-0.0831		0.0414
		(0.0507)		(0.0327)
Post × High HHI Industry		-0.0788		-0.1054***
		(0.0673)		(0.0313)
Post × Horizontal		0.0199		-0.0266
		(0.0478)		(0.0350)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of patents based on equation 7. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in a given year. The *Post* dummy indicates the years after the M&A event. The $High\,Impact$ dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The $High\,Synergy$ dummy indicates high potential innovation synergies between the target and the acquirer. The $High\,Text\,Similarity$ dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The $High\,HHI\,Industry$ dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The $Horizontal$ dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the Pre dummy indicating pre-merger periods, the $High\,Impact$ dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the $High\,Synergy$ dummy, the $High\,Text\,Similarity$ dummy, the $High\,HHI\,Industry$ dummy, the $Horizontal$ dummy, and their interactions with the Pre dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 3: Changes in Patent Quality Measured by Citations around M&As

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

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of high-citation and low-citation patents based on equation 7. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. In columns 1 and 3, the dependent variable is the difference between the number of patents with above-median citations (normalized by patent class and grant year) filed by the treated inventor and the number of patents with above-median citations filed by the matched counterfactual inventor. In columns 2 and 4, the dependent variable is the difference between the number of patents with below-median citations filed by the treated inventor and the number of patents with below-median citations filed by the matched counterfactual inventor. The *Post* dummy indicates the years after the M&A event. The $High\,Impact$ dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The $High\,Synergy$ dummy indicates high potential innovation synergies between the target and the acquirer. The $High\,Text\,Similarity$ dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The $High\,HHI\,Industry$ dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The $Horizontal$ dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the Pre dummy indicating pre-merger periods, the $High\,Impact$ dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the $High\,Synergy$ dummy, the $High\,Text\,Similarity$ dummy, the $High\,HHI\,Industry$ dummy, the $Horizontal$ dummy, and their interactions with the Pre dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 4: Changes in Inventors' Earnings around M&As

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

This table reports difference-in-differences estimates of the effect of M&As on inventors' earnings based on equation 7. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings. The *Post* dummy indicates the years after the M&A event. The *High Impact* dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High HHI Industry* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Impact* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High HHI Industry* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 5: Changes in Inventors' Separation Rates around M&As

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

This table reports difference-in-differences estimates of the effect of M&As on inventors' separation rates based on equation 7. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference in separation dummy between the treated inventor and the matched counterfactual inventor, where the separation dummy equals one if the inventor is no longer employed by the dominant employer in year -1. The *Post* dummy indicates the years after the M&A event. The $High\,Impact$ dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The $High\,Synergy$ dummy indicates high potential innovation synergies between the target and the acquirer. The $High\,Text\,Similarity$ dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The $High\,HHI\,Industry$ dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The $Horizontal$ dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the Pre dummy indicating pre-merger periods, the $High\,Impact$ dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the $High\,Synergy$ dummy, the $High\,Text\,Similarity$ dummy, the $High\,HHI\,Industry$ dummy, the $Horizontal$ dummy, and their interactions with the Pre dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 6: Changes in Inventor Outcomes around M&As Controlling for Firm and Commuting Zone Fixed Effects

Panel A: Target Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0115	0.0426	0.0324	0.0430	0.3806***	0.4389***
	(0.0686)	(0.0764)	(0.0247)	(0.0291)	(0.0692)	(0.0680)
Post × High Impact	-0.1042*	-0.0773	-0.0136	-0.0048	-0.0471*	-0.0198
	(0.0620)	(0.0701)	(0.0162)	(0.0188)	(0.0240)	(0.0222)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm×CZ FE	No	Yes	No	Yes	No	Yes
Obs	160,000	160,000	160,000	160,000	96,000	96,000

Panel B: Acquirer Inventors

	Number of Patents		Log Annual Earnings		Separation Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0275	0.0262	0.0087	0.0090	-0.2004***	-0.2101***
	(0.0357)	(0.0356)	(0.0186)	(0.0185)	(0.0132)	(0.0124)
Post × High Impact	-0.0990***	-0.0928**	-0.0314**	-0.0299**	-0.0345***	-0.0339***
	(0.0363)	(0.0362)	(0.0136)	(0.0137)	(0.0118)	(0.0117)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm×CZ FE	No	Yes	No	Yes	No	Yes
Obs	2,210,000	2,210,000	2,210,000	2,210,000	1,350,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes with firm fixed effects or firm-by-commuting-zone fixed effects. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in columns 1 and 2, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in columns 3 and 4, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in columns 5 and 6. The *Post* dummy indicates the years after the M&A event. The *High Impact* dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. We control for the *Pre* dummy indicating pre-merger periods, the *High Impact* dummy, and the interaction of the two dummies in all columns. All columns include firm fixed effects (where firm is the dominant employer in year $t-1$), and columns 2, 4, and 6 additionally include firm-by-commuting zone fixed effects. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 7: Impact on Innovation Concentration and Changes in Inventor Outcomes around M&As

Panel A: Target Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	-0.0195	-0.0051	0.0615***
	(0.0355)	(0.0194)	(0.0238)
Post × High Impact	-0.1304**	-0.0340*	-0.0745***
	(0.0540)	(0.0187)	(0.0237)
Post × High Impact on Innovation Concentration	-0.0046	-0.0101	0.0150
	(0.0557)	(0.0163)	(0.0210)
Post × High Synergy	0.1938**	-0.0618*	-0.0159
	(0.0779)	(0.0348)	(0.0480)
Post × High Text Similarity	-0.0821	0.0083	-0.0843**
	(0.0542)	(0.0282)	(0.0329)
Post × High HHI Industry	-0.0790	-0.0181	0.0467
	(0.0669)	(0.0244)	(0.0347)
Post × Horizontal	0.0202	-0.0214	-0.0179
	(0.0477)	(0.0235)	(0.0312)
Obs	160,000	160,000	96,000

Panel B: Acquirer Inventors

	Number of Patents	Log Annual Earnings	Separation Rate
	(1)	(2)	(3)
Post	0.0139	-0.0172	-0.1011***
	(0.0342)	(0.0155)	(0.0149)
Post × High Impact	-0.1108***	-0.0224*	-0.0469***
	(0.0381)	(0.0122)	(0.0136)
Post × High Impact on Innovation Concentration	0.0363	-0.0448**	0.0388
	(0.0501)	(0.0177)	(0.0275)
Post × High Synergy	0.0300	-0.0405**	0.0586**
	(0.0489)	(0.0183)	(0.0234)
Post × High Text Similarity	0.0365	-0.0046	0.0276*
	(0.0329)	(0.0138)	(0.0146)
Post × High HHI Industry	-0.1037***	0.0016	-0.0102
	(0.0314)	(0.0127)	(0.0146)
Post × Horizontal	-0.0272	-0.0258	0.0058
	(0.0350)	(0.0160)	(0.0183)
Obs	2,210,000	2,210,000	1,350,000

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes controlling for the impact of M&As on innovation concentration. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. The $Innovation\,Concentration$ dummy indicates that the merger has a high predicted impact on innovation concentration defined using market shares based on the number of patents within each technology class (see details in Section 4.4). Other variables are defined as in Table 2. We control for the Pre dummy indicating pre-merger periods, the $High\,Impact$ dummy, the $Innovation\,Concentration$ dummy, the $High\,Synergy$ dummy, the $High\,Text\,Similarity$ dummy, the $High\,HHI\,Industry$ dummy, the $Horizontal$ dummy, and their interactions with the Pre dummy in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table 8: Changes in Inventor Outcomes around Failed Mergers

Panel A: Target Inventors

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

Panel B: Acquirer Inventors

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

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

Table 9: Merger Premiums and Post-merger Returns of High-Impact and High-Synergy M&As

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

This table reports OLS estimates of regressing financial outcomes of mergers (merger premiums or post-merger returns) on merger characteristics (labor market impact and synergy). Each observation is a merger event. In column 1, the dependent variable is merger premium, defined as the ratio of the offer price to the target's stock price 1 day before the merger announcement. In columns 2 to 6, the dependent variables are log changes in the acquirer's stock price from 1 day before the merger announcement to 1 day, 1 week, 4 weeks, 60 days, or 90 days after merger announcement. *Average High Impact* is the average *High Impact* dummy for all inventors involved in the merger, where the *High Impact* dummy indicates that the merger a high predicted impact on the labor market concentration of the inventor. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. Standard errors are clustered at the event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Internet Appendix

A. 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 inventor 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 1. 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 $\partial\beta^w/\partial r \geq 0$.

Proof of Proposition 2. We show that when there is low synergy ($r \leq v$), firms find it optimal to merge when $\beta \geq \beta_c$. (If synergy is high, firm profits are even higher when they merge and this is also true.)

The profits of the merged firm is:

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

In the stand-alone case, each firm's profit is:

$$\pi^{S*} = e^{S*}(1-e^{S*})(1-\beta)(1-\delta)M$$

The gains from merger is:

$$\Delta\pi = \pi^{M*} - 2\pi^{S*}$$

When $\beta = 1$, the gains from merger is:

$$\Delta\pi(\beta = 1) = (1 - v)\frac{M^3}{(k + (1 - v)M)^2} > 0$$

Since $\Delta\pi$ is continuous in β, it follows that there exists $\beta_c \in [0, 1)$ such that $\Delta\pi > 0$ for $\beta < \beta_c$.

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 inventors 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.

A.3. Numerical Exercise

To illustrate how inventor efforts, firm profits, and total surpluses change under different parameters, we conduct a numerical exercise with different values of labor market power v and employee bargaining power β in Appendix Figures A1 to A3. In all of the figures, we set $M = 1$, $k = 2$, and $\delta = 0.5$. We assume that there is no competition loss in the product market (i.e., $d = 0.5$) and there is no synergy (i.e., $r = 0$). We consider three different values of β: 0.1, 0.3, and 0.6. The value of employee bargaining power ranges from 0 to 0.5 (since the model requires that $v \leq d$).

In each figure, Panel (a) plots the optimal effort level of each inventor under stand-alone and merger cases. Panel (b) plots the total profit of the two stand-alone firms (π^{S*}), the profit of the merging firm (π^{M*}), and the counterfactual profit of the merging firm if the effort level is the same as the stand-alone case. Panel (c) plots the total expected surplus of the firms and inventors. In the stand-alone case, the total surplus is $2\pi^{S*} + 2w^{S*}$; in the merger case, the total surplus is $\pi^{M*} + 2w^{M*}$. Panel (d) plots the effect of merger on firm profit ($\pi^{M*} - 2\pi^{S*}$) and total surplus ($\pi^{M*} - 2\pi^{S*} + 2w^{M*} - 2w^{S*}$).

We note a few observations from the numerical exercise:

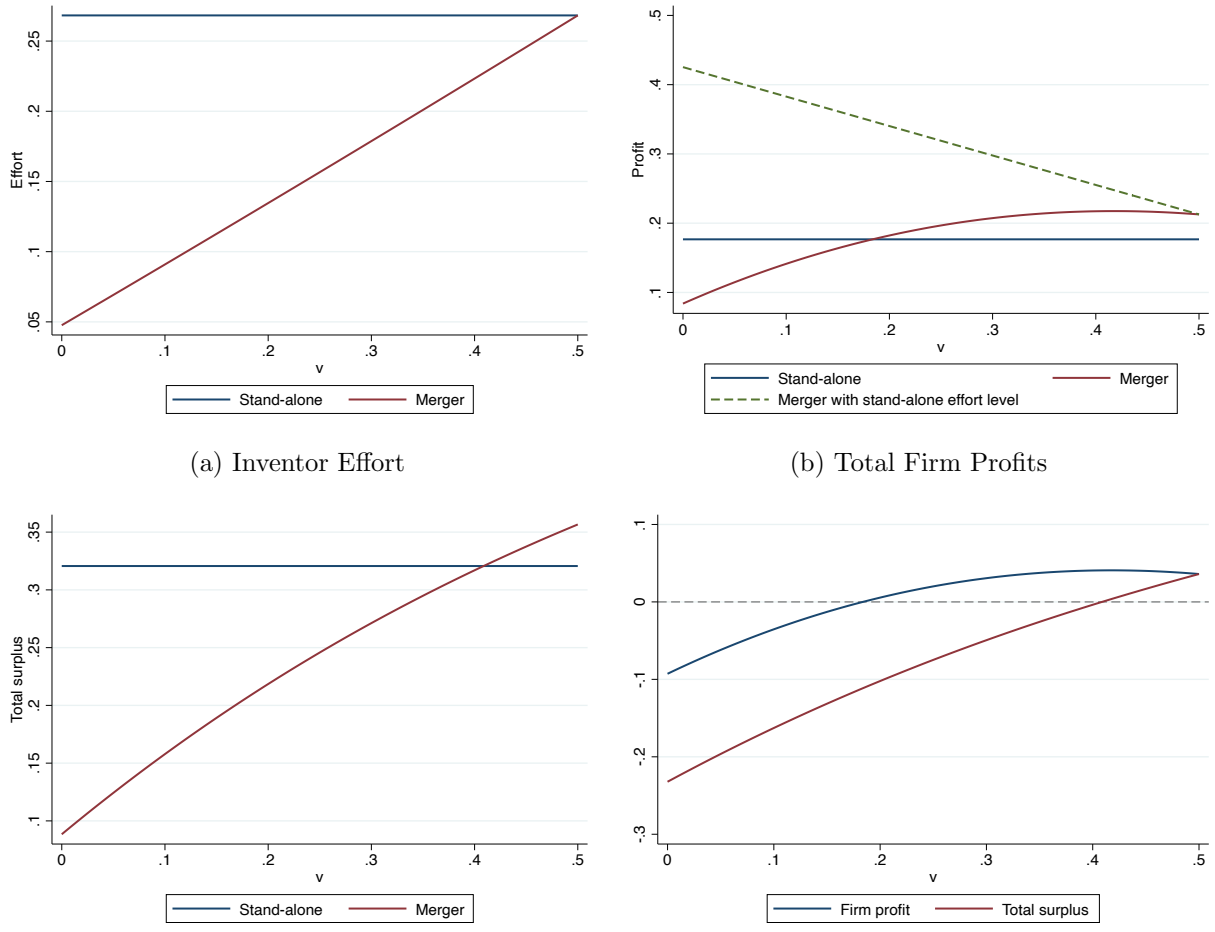
1. Merger always reduces inventor effort when there is no synergy (Corollary 1). Inventor effort under merger is monotonically increasing in inventors' outside option v (Corollary 2).

2. Firm profit under merger is not monotonic in inventors' outside option v. This is because of two countervailing forces: lower outside options decrease inventor effort and profits, and lower outside options allow firms to extract more rents and increase profits (as shown by the counterfactual profit monotonically decreasing in v when keeping inventor effort fixed in Panel (b)). When β is small, inventors have weak incentives, and the merged firm's profit is increasing in outside options which increase inventor incentives. When β is larges, inventor incentives are already very strong, and the merged firm's profit is decreasing in outside options which reduce the rents the firm can extract.

3. It is optimal for firms to merge when β is big and optimal for firms to remain stand-alone when β is small (Proposition 2). The profit gain from merger is non-monotonic in inventors' outside options.

4. Merger can reduce total surplus even when firms find it optimal to merge, because firms do not internalize the negative impact of merger on inventor payoffs. This is especially true when inventors' outside option v is low and firms have strong labor market power.

Figure A1: Effort, Profit, and Surplus When $\beta = 0.1$



(a) Inventor Effort

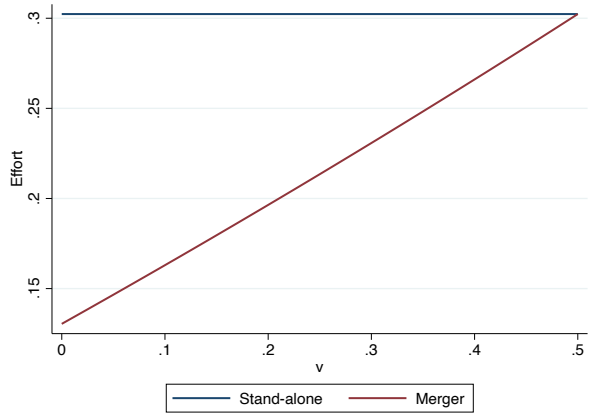
(b) Total Firm Profits

(c) Total Surplus

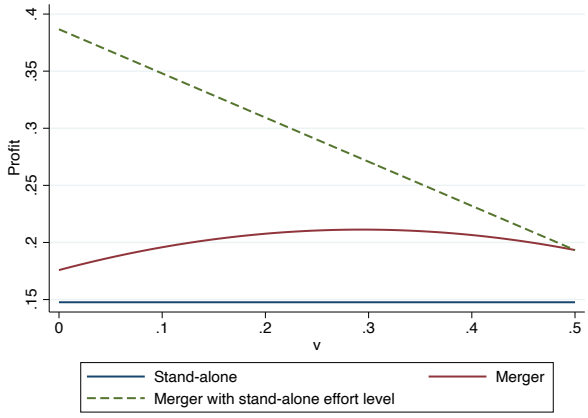
(d) Effect of Merger on Firm Profit and Total Surplus

This figure plots inventor effort (Panel (a)), total firm profit (Panel (b)), and total surplus of all firms and inventors (Panel (c)) under two stand-alone firms and one merged firm. In Panel (b), we also plot the counterfactual profit of the merged firm if keeping inventor effort at the same level as under stand-alone firms. Panel (d) plots the changes in total firm profit and total surplus when two stand-alone firms merge. We set $M = 1$, $k = 2$, $\delta = 0.5$, $d = 0.5$, $r = 0$, and $\beta = 0.1$.

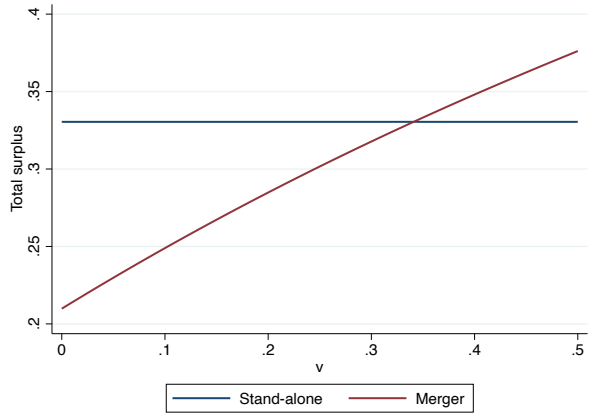
Figure A2: Effort, Profit, and Surplus When $\beta = 0.3$



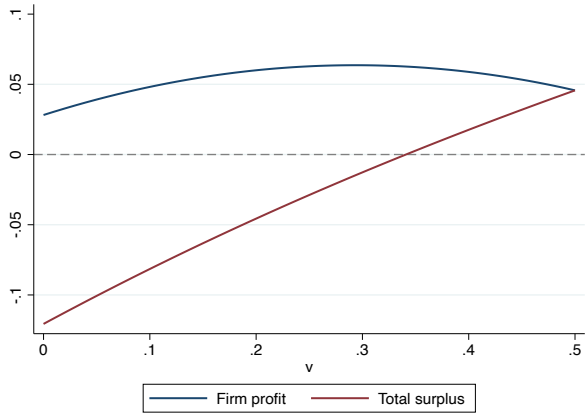
(a) Inventor Effort



(b) Total Firm Profits



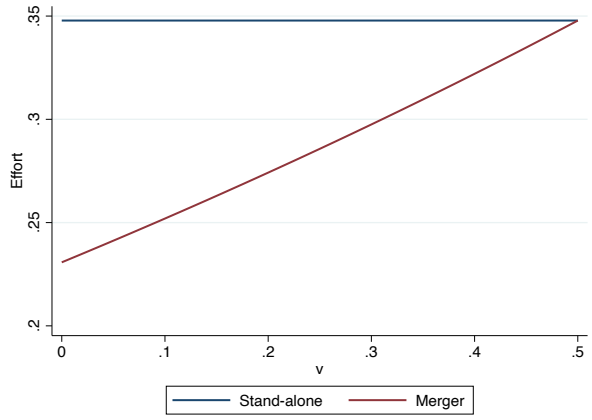
(c) Total Surplus



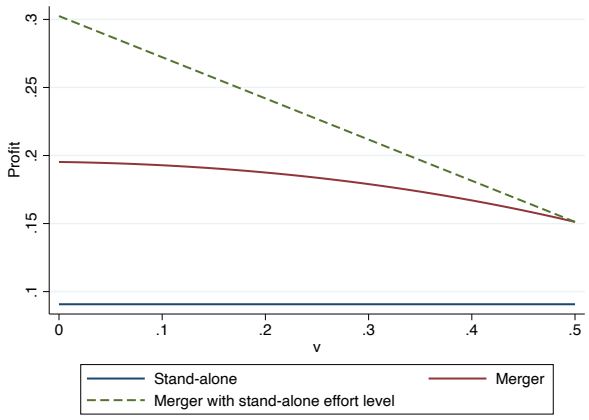
(d) Effect of Merger on Firm Profit and Total Surplus

This figure plots inventor effort (Panel (a)), total firm profit (Panel (b)), and total surplus of all firms and inventors (Panel (c)) under two stand-alone firms and one merged firm. In Panel (b), we also plot the counterfactual profit of the merged firm if keeping inventor effort at the same level as under stand-alone firms. Panel (d) plots the changes in total firm profit and total surplus when two stand-alone firms merge. We set $M = 1$, $k = 2$, $\delta = 0.5$, $d = 0.5$, $r = 0$, and $\beta = 0.3$.

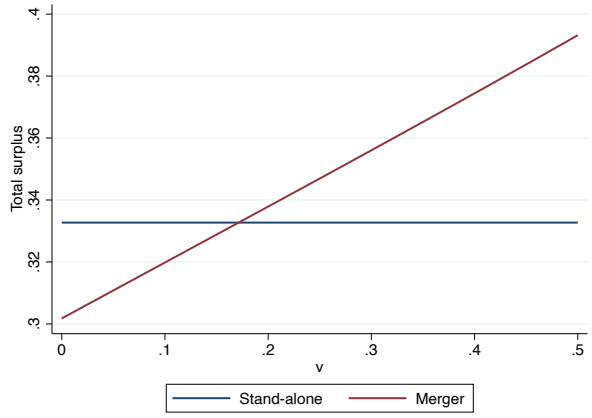
Figure A3: Effort, Profit, and Surplus When $\beta = 0.6$



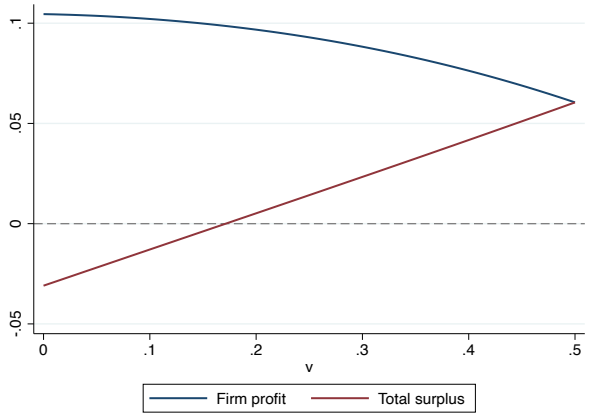
(a) Inventor Effort



(b) Total Firm Profits



(c) Total Surplus



(d) Effect of Merger on Firm Profit and Total Surplus

This figure plots inventor effort (Panel (a)), total firm profit (Panel (b)), and total surplus of all firms and inventors (Panel (c)) under two stand-alone firms and one merged firm. In Panel (b), we also plot the counterfactual profit of the merged firm if keeping inventor effort at the same level as under stand-alone firms. Panel (d) plots the changes in total firm profit and total surplus when two stand-alone firms merge. We set $M = 1$, $k = 2$, $\delta = 0.5$, $d = 0.5$, $r = 0$, and $\beta = 0.6$.

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.[33] By applying this technique, the free-form text of a patent is transformed into a vector of TF-IDF-weighted terms. The similarity between any two patents is then calculated by measuring the cosine distance between their respective vectors, which ranges from zero (completely dissimilar) to one (identical). This vector-based approach provides an automated measure of similarity between patents, enhancing the ability to quantify the relationship between innovations. This method offers significant improvement over citation-based measures, where the connection between patents depends on the inventors' awareness of prior art and the discretion of patent examiners to cite related patents. By using TF-IDF, we eliminate the biases associated with citation practices and create a more consistent and objective measure of innovation similarity.

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

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

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

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

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

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

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

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

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

B.3. Commuting Zone of Inventors

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

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

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

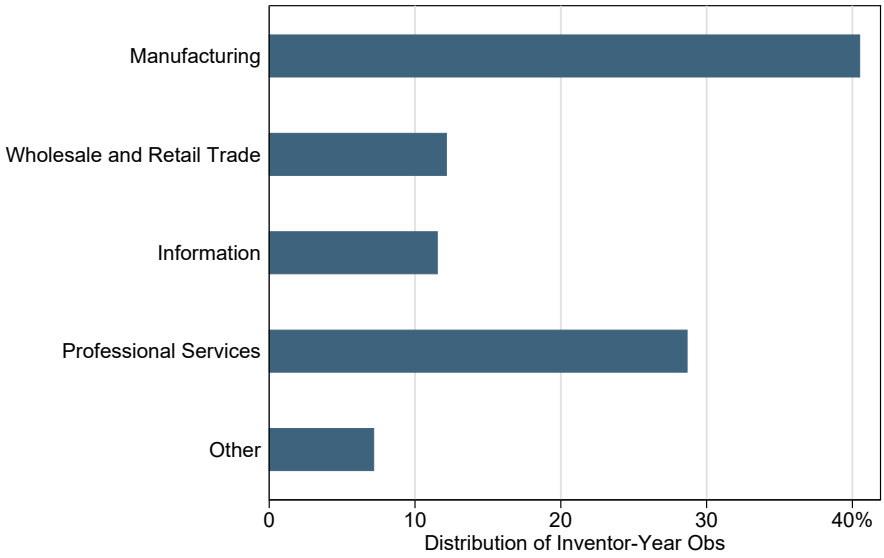
B.4. Patent Quality Measures

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

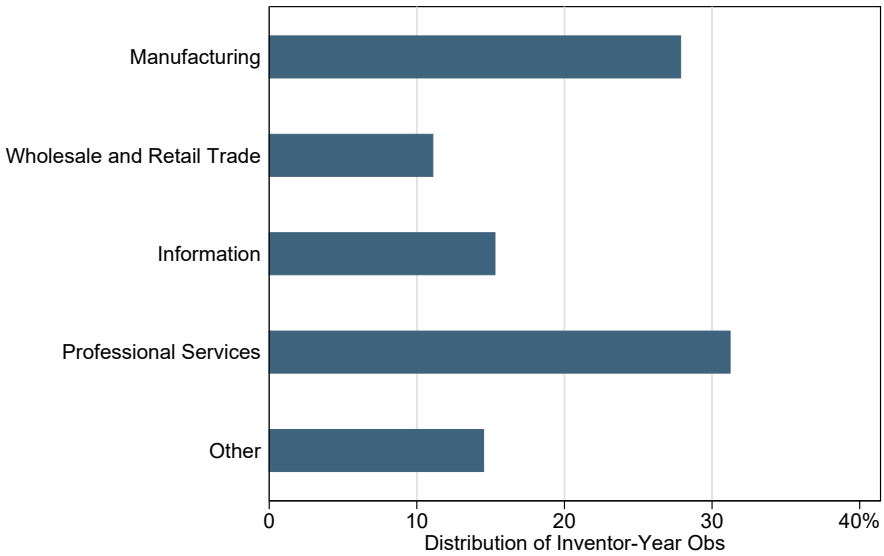
Generality. A high generality score indicates that the patent influenced subsequent innovations in a variety of fields. Generality for patent i is defined as $1 - \sum_j s_{ij}^2$, where s_{ij} is the percentage of citations received by patent i that belong to patent class j. Thus, if a patent is cited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

C. Additional Tables and Figures

Figure A4: Distribution of Inventors by Industry Sector



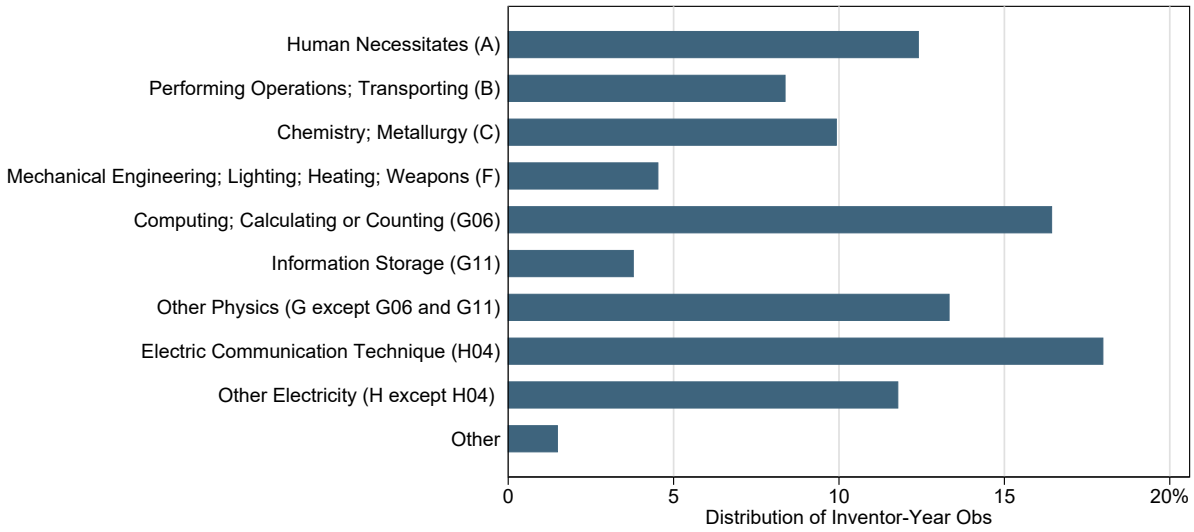
(a) Target Inventors



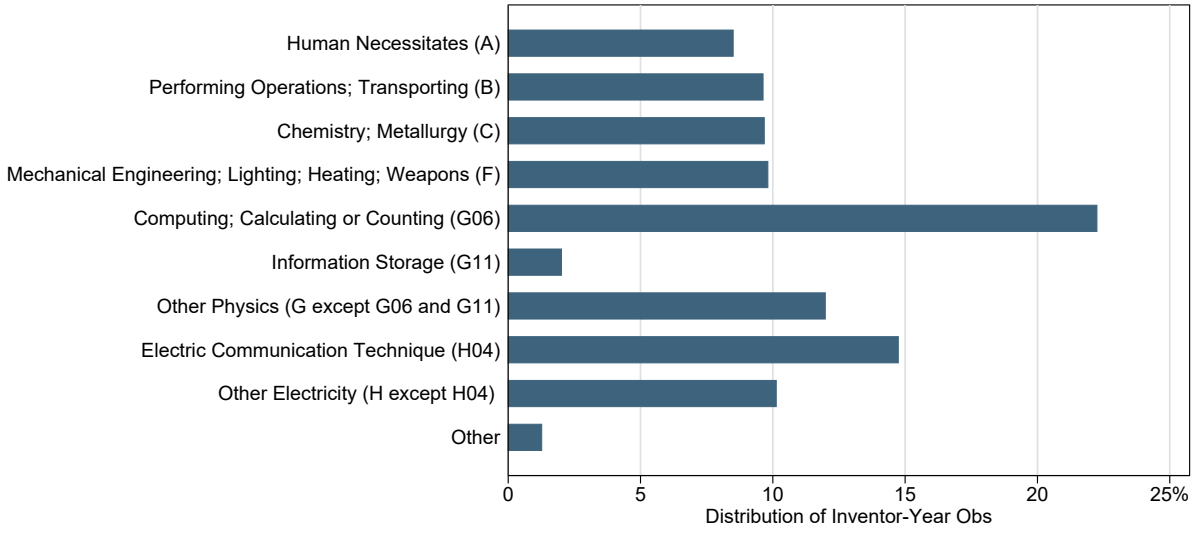
(b) Acquirer Inventors

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

Figure A5: Distribution of Inventors by Technological Field



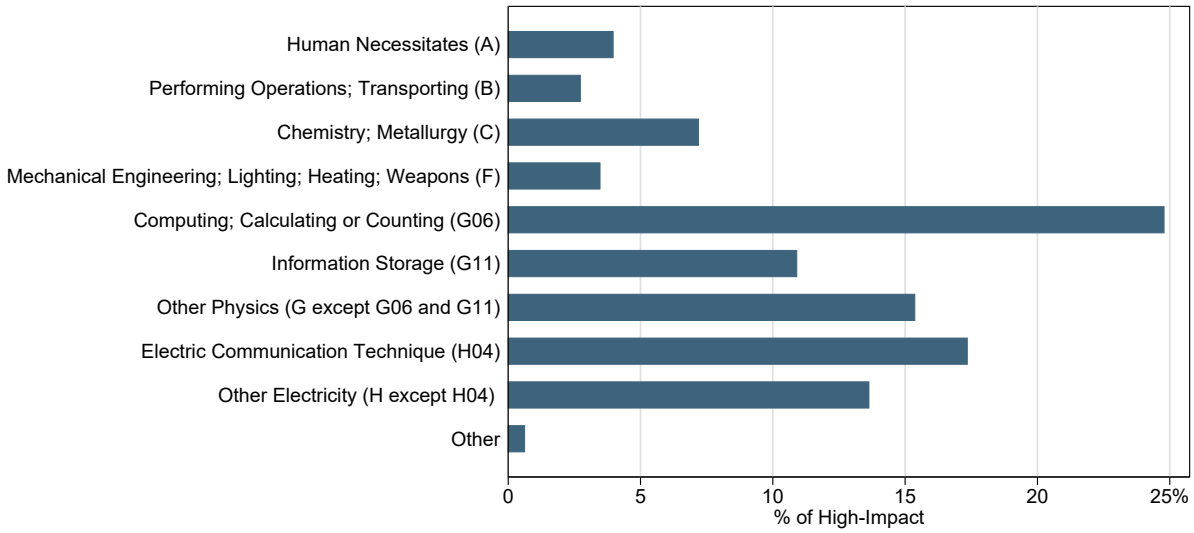
(a) Target Inventors



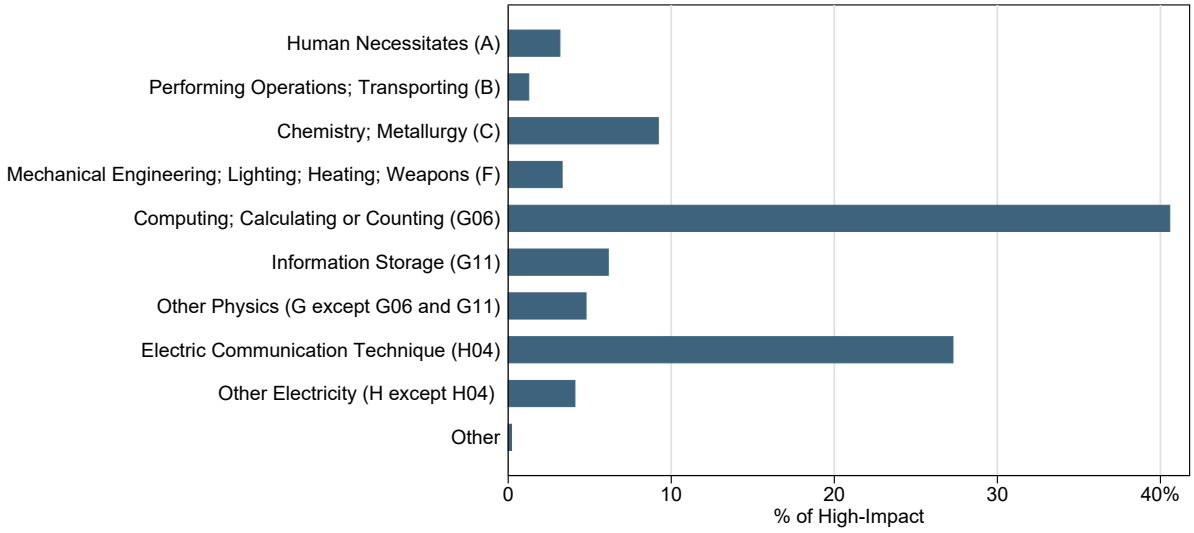
(b) Acquirer Inventors

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

Figure A6: Distribution of High-Impact Inventors by Technological Field



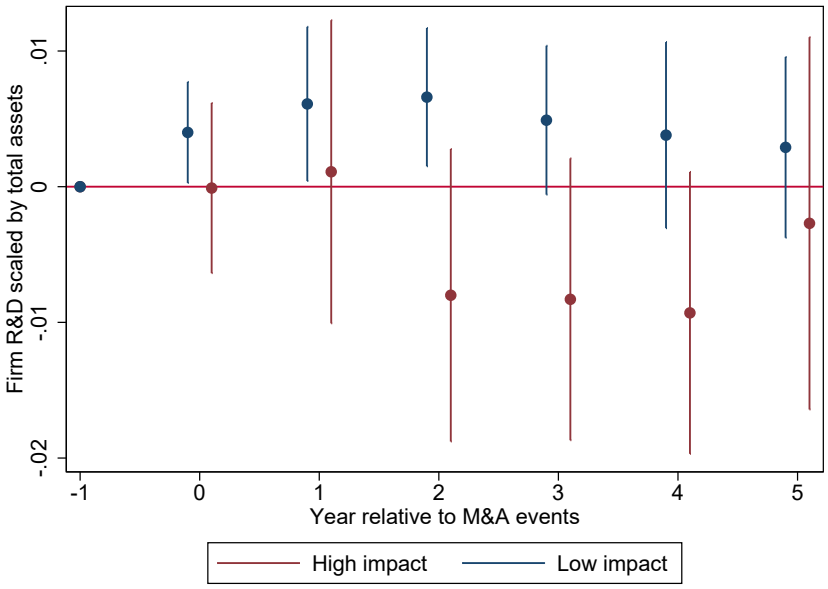
(a) Target Inventors



(b) Acquirer Inventors

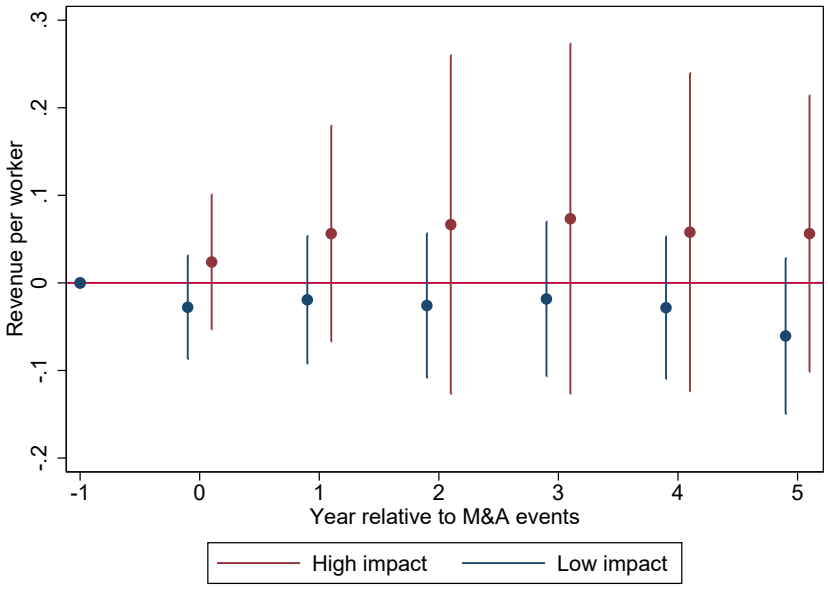
This figure plots the distribution of high-impact inventors (inventors experiencing M&As with a high predicted impact on labor market concentration) in our sample by technological fields. Each inventor is assigned to a primary field based on the area in which they filed the most patents during the five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

Figure A7: Changes in Firm R&D around M&As



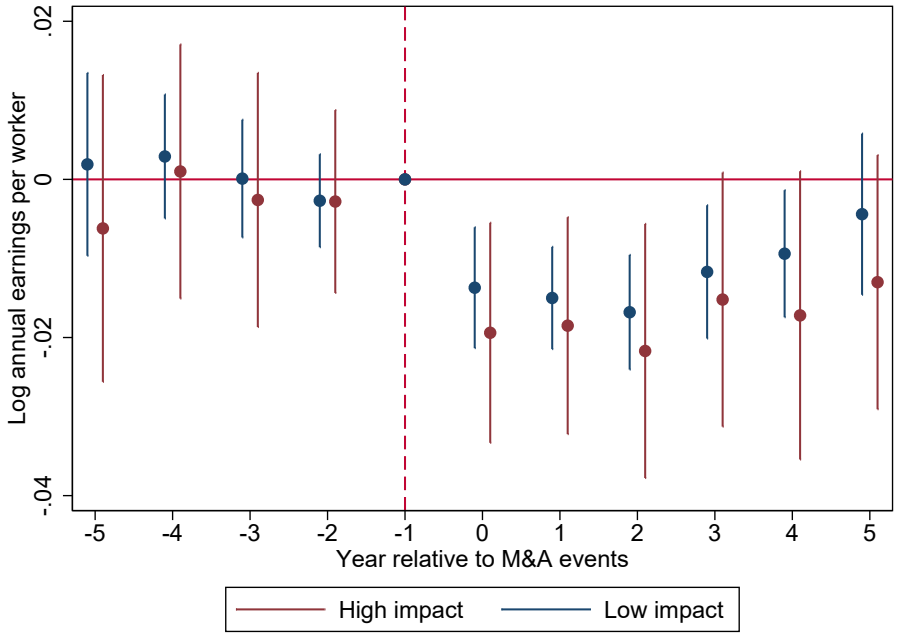
This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on R&D of the merged firm by high-impact and low-impact inventors based on equation 8. The dependent variable is firm-level R&D expenditure over lagged total assets of the inventor's employer (both R&D and total assets are from the Compustat data).

Figure A8: Changes in Firm Labor Productivity around M&As

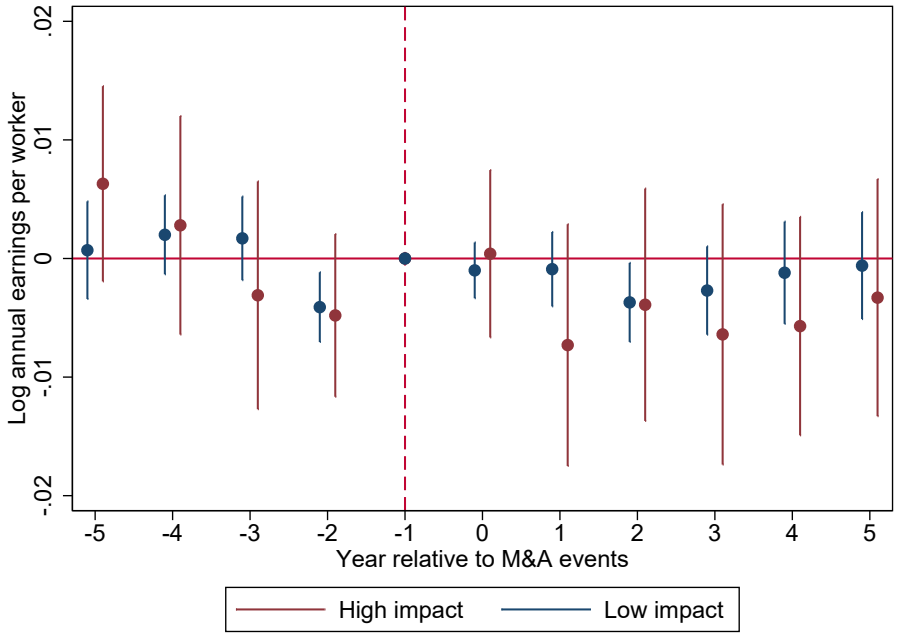


This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on revenue per worker of the merged firm by high-impact and low-impact inventors based on equation 8. The dependent variable is firm-level log revenue per worker of the inventor's employer (firm-level revenue and employment are from the LBD data).

Figure A9: Changes in Firm Average Wage around M&As



(a) Target Inventors



(b) Acquirer Inventors

This figure plots event-study estimates and 95% confidence intervals for the impact of M&As on firm average wage by high-impact and low-impact inventors based on equation 8. The dependent variable is log earnings per worker (total wage bill divided by employment) of the inventor's establishment.

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

	Target Inventors		Acquirer Inventors	
	Number of High-Originality Patents	Number of Low-Originality Patents	Number of High-Originality Patents	Number of Low-Originality Patents
	(1)	(2)	(3)	(4)
Post	0.0014	-0.0209	0.0017	0.0118
	(0.0225)	(0.0280)	(0.0169)	(0.0240)
Post × High Impact	-0.0605*	-0.0716	-0.0118	-0.0906***
	(0.0311)	(0.0466)	(0.0175)	(0.0255)
Post × High Synergy	0.1103**	0.0816	0.0130	0.0224
	(0.0547)	(0.0585)	(0.0265)	(0.0310)
Post × High Text Similarity	-0.0314	-0.0517	0.0233	0.0180
	(0.0314)	(0.0354)	(0.0169)	(0.0216)
Post × High HHI Industry	-0.0307	-0.0481	-0.0492***	-0.0561***
	(0.0369)	(0.0462)	(0.0166)	(0.0195)
Post × Horizontal	-0.0104	0.0304	-0.0004	-0.0261
	(0.0292)	(0.0322)	(0.0200)	(0.0225)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of high-originality and low-originality patents based on equation 7. Originality is defined in Appendix B.4. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. In columns 1 and 3, the dependent variable is the difference between the number of patents with above-median originality filed by the treated inventor and the number of patents with above-median originality filed by the matched counterfactual inventor. In columns 2 and 4, the dependent variable is the difference between the number of patents with below-median originality filed by the treated inventor and the number of patents with below-median originality filed by the matched counterfactual inventor. The *Post* dummy indicates the years after the M&A event. The $High\,Impact$ dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The $High\,Synergy$ dummy indicates high potential innovation synergies between the target and the acquirer. The $High\,Text\,Similarity$ dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The $High\,HHI\,Industry$ dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The $Horizontal$ dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the Pre dummy indicating pre-merger periods, the $High\,Impact$ dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the $High\,Synergy$ dummy, the $High\,Text\,Similarity$ dummy, the $High\,HHI\,Industry$ dummy, the $Horizontal$ dummy, and their interactions with the Pre dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A2: Changes in Patent Quality Measured by Generality around M&As

	Target Inventors		Acquirer Inventors	
	Number of High-Generality Patents	Number of Low-Generality Patents	Number of High-Generality Patents	Number of Low-Generality Patents
	(1)	(2)	(3)	(4)
Post	-0.0082	-0.0113	-0.0039	0.0174
	(0.0213)	(0.0269)	(0.0211)	(0.0235)
Post × High Impact	-0.0391	-0.0930*	-0.0323*	-0.0701***
	(0.0313)	(0.0485)	(0.0184)	(0.0265)
Post × High Synergy	0.0956**	0.0963*	0.0236	0.0118
	(0.0408)	(0.0518)	(0.0248)	(0.0372)
Post × High Text Similarity	0.0080	-0.0911***	0.0408**	0.0005
	(0.0333)	(0.0335)	(0.0180)	(0.0248)
Post × High HHI Industry	-0.0881*	0.0093	-0.0443***	-0.0610**
	(0.0459)	(0.0329)	(0.0153)	(0.0248)
Post × Horizontal	0.0315	-0.0116	-0.0029	-0.0236
	(0.0300)	(0.0359)	(0.0193)	(0.0264)
Obs	160,000	160,000	2,210,000	2,210,000

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of high-generality and low-generality patents based on equation 7. Generality is defined in Appendix B.4. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. In columns 1 and 3, the dependent variable is the difference between the number of patents with above-median generality filed by the treated inventor and the number of patents with above-median generality filed by the matched counterfactual inventor. In columns 2 and 4, the dependent variable is the difference between the number of patents with below-median generality filed by the treated inventor and the number of patents with below-median generality filed by the matched counterfactual inventor. The *Post* dummy indicates the years after the M&A event. The *High Impact* dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The *High Synergy* dummy indicates high potential innovation synergies between the target and the acquirer. The *High Text Similarity* dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The *High HHI Industry* dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The *Horizontal* dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the *Pre* dummy indicating pre-merger periods, the *High Impact* dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the *High Synergy* dummy, the *High Text Similarity* dummy, the *High HHI Industry* dummy, the *Horizontal* dummy, and their interactions with the *Pre* dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A3: Heterogeneous Effects of M&As on Inventors by Pre-merger Inventor Characteristics

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

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

Table A4: Heterogeneous Effects of M&As on Inventors by Pre-merger Firm Characteristics

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

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

Table A5: Effects of M&As on High-Impact Inventors Using Alternative Labor Market Concentration Measures

Panel A: Using 3-Digit CPC Technology Class.

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

Panel B: 1% Threshold for Geographical Markets.

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

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

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

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

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

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

Table A6: Change in the Number of Patents around Spinoffs

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

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

Table A7: Effects of M&As on Inventors When Matching Treated Inventors to Counterfactual Inventors Three Years Before the Merger

Panel A: Target Inventors

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

Panel B: Acquirer Inventors

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

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

Table A8: Average Effect of M&As on Inventor Outcomes

Panel A: Target Inventors

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

Panel B: Acquirer Inventors

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

This table reports difference-in-differences estimates of the effect of M&As on inventors outcomes based on equation 10. Panel A shows the estimates for target inventors and Panel B shows the estimates for acquirer inventors. In each panel, the dependent variables are the difference between the number of patents filed by the treated inventor and the number of patents filed by the matched counterfactual inventor in column 1, the difference between the treated inventor's log annual earnings and the matched counterfactual inventor's log annual earnings in column 2, and the difference in separation dummy between the treated inventor and the matched counterfactual inventor in column 3. The *Post* dummy indicates the years after the merger. We control for the *Pre* dummy indicating pre-merger periods in all columns. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).

Table A9: Changes in the Number of Patents Belonging to the Original Employer around M&As

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

This table reports difference-in-differences estimates of the effect of M&As on inventors' number of patents belonging to the original employer in year -1 based on equation 7. Columns 1 and 2 show the estimates for target inventors and columns 3 and 4 show the estimates for acquirer inventors. The dependent variable is the difference between the number of patents filed by the treated inventor and belonging to the original employer and the number of patents filed by the matched counterfactual inventor and belonging to the original employer in a given year (if the inventor switches employer between year -1 and a given year, the number of patents belonging to the original employer is set to zero). The *Post* dummy indicates the years after the M&A event. The $High\,Impact$ dummy indicates that the merger has a high predicted impact on the labor market concentration of the inventor. The $High\,Synergy$ dummy indicates high potential innovation synergies between the target and the acquirer. The $High\,Text\,Similarity$ dummy indicates high innovation substitutability based on textual similarity between patents of the target and the acquirer. The $High\,HHI\,Industry$ dummy indicates that the target or the acquirer firm is in a high-concentration 4-digit NAICS industry. The $Horizontal$ dummy indicates horizontal mergers where the target and the acquirer firms are in the same 4-digit NAICS industry. We control for the Pre dummy indicating pre-merger periods, the $High\,Impact$ dummy, and the interaction of the two dummies in all columns. In columns 2 and 4, we also control for the $High\,Synergy$ dummy, the $High\,Text\,Similarity$ dummy, the $High\,HHI\,Industry$ dummy, the $Horizontal$ dummy, and their interactions with the Pre dummy. Standard errors are clustered at the firm-event level. Stars denote standard statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively).