The Value of Internal Labor Markets: Evidence from LinkedIn Profiles and U.S. Inventors*

Letian Zhang†

Simeng Wang‡

Forthcoming in *American Journal of Sociology*

Abstract

This paper proposes a new measure for an organization's internal career ladder. Analyzing job-to-job movements in LinkedIn profiles, we measure the extent to which an organization relies on internal versus external hiring. We then use this newly constructed measure to revisit the classic sociological question about the value of internal labor markets. Matching LinkedIn profiles of 446,058 U.S. inventors and tracking their performance from 2000 to 2025, we find that inventors are more productive when their employers have higher rates of internal promotion. However, this pattern largely disappears among inventors nearing the end of their careers, suggesting the importance of career advancement incentives. This study leverages LinkedIn data to provide new evidence on the value of internal labor markets.

Keywords: career ladders, promotion, innovation, employee performance, human capital

*We thank Matthew Bidwell, Kathryn Dlugos, Daniel Keum, Kunyuan Qiao, David Li, the anonymous reviewers, and participants in the Greater Boston Corporate Governance Workshop, Wharton's People and Organization Conference, and Equity by Design Lab for their valuable feedback.

†Kellogg School of Management, Northwestern University. Correspondence: letian.lt.zhang@gmail.com.

‡Columbia Business School, Columbia University.

1. INTRODUCTION

A long-standing question in organizational sociology is the value of internal labor markets. Max Weber ([1922] 2019) highlighted the role of bureaucratic structures and career ladders in maintaining order and motivating employees. Peter Blau and W. Richard Scott (1962) and James March and Herbert Simon (1958) suggested that formal structures shape behavior and incentives inside organizations. Building on this tradition, Kalleberg (1977) argued that limited promotion opportunities can discourage initiative and lower morale. Doeringer and Piore (1971) also stressed how internal labor markets create stable career paths and reduce turnover. At the same time, scholars have noted that firms' reliance on external hiring makes the employer-employee relationship more transactional. This can weaken loyalty, reduce long-term commitment, and ultimately hurt performance (Kalleberg & Marsden 2013; Tolbert 1996).

Yet empirical evidence on these theories is limited. Most studies compare the performance of workers who are promoted internally with those hired from outside (Chang 2023; Chan 2006; Bertheau 2021; Bayo-Moriones and Ortín-Ángel 2006; DeVaro and Morita 2013; Agrawal et al. 2006; Keller et al. 2021; Keller 2018; Dlugos and Keller 2021; Keller and Dlugos 2023; DeVaro et al. 2019; Bidwell and Mollick 2015), but few studies consider whether internal promotion rates are associated with performance in the broader workforce. A major obstacle is measurement. Firms rarely release data on internal moves, and public datasets often lack the details—such as timing, job titles, or reporting lines—needed to trace promotion paths. As a result, while the value of internal labor markets is often discussed, large-scale evidence remains scarce.

This study introduces a scalable measure of organizations' internal career ladders using publicly available LinkedIn profiles. Using a near-universe of profiles, we infer vacancies and classify whether roles are filled through internal promotion or external hiring. We first compare LinkedIn's workforce composition with nationally representative sources—the

American Community Survey at the industry-year level and the restricted EEO-1 at the firm–year level. We then compare our promotion measure with alternative indicators of internal mobility, including the share of external job postings across ranks, employee reviews on promotion opportunities, and administrative statistics from the New York City government.

After evaluating our measure, we apply it to study the link between the internal labor market of firms and the performance of their employees. To do this, we matched LinkedIn profiles with U.S. inventors listed in the Patent and Trademark Office (USPTO) database, based on individual names and employer information. This matched dataset covers the full career histories of 446,058 inventors in the United States. We calculate, at the firm-year level, the share of inventors being internally promoted or externally hired, excluding the focal inventor.

We find that inventors are more productive in firms with higher rates of internal promotion. With inventor–title fixed effects, a one–standard deviation increase in a firm's internal promotion rate is associated with roughly 1.8 percent more citations per inventor. In contrast, inventors produce patents with fewer citations when their firms rely more heavily on external hiring. We also compare inventors who began at the same firm but later moved to different organizations. While their productivity followed similar trends before the move, their paths diverged afterward. Those who joined firms with higher internal promotion rates on average showed clear gains in productivity relative to their peers.

We find a similar pattern, albeit a smaller effect size, when including fixed effects on individual-title-employer-location. These models observe productivity changes in the same inventor working in the same job at the same firm, with the only variation coming from changes in that firm's internal hiring rate. We also replicate our findings using a variety of model specifications, including alternative measures of internal hiring rates, various ways of quantifying inventors' innovation output, and different sample cuts.

Next, we examine whether the link between internal hiring rates and inventor performance varies by career stage. Inventors in later stages may care less about advancement opportunities. Consistent with this idea, we find that our pattern holds only for mid- and early-career inventors. For those near retirement, a firm's internal hiring rate shows little or no relationship with their productivity.

We have thus far shown that the use of internal hiring is associated with more productivity among employees who have not experienced a job change. But it is possible that external hires significantly outperform internal hires, such that their higher performance overcomes the performance premium of internal hiring on other employees. To explore this possibility, we directly compare the performance of internally promoted and externally hired inventors in the same firm with the same job title. We find internally promoted inventors to outperform externally hired inventors by more than 30 percent in their first year on the job, although this difference becomes smaller as inventors spend more time on the job. These findings further suggest that organizations may benefit more by focusing on internal instead of external hiring.

This study introduces a way to measure organizations' internal labor markets and applies it to the classic sociological question of their value. While we do not claim causal identification, we provide large-scale evidence of a positive relationship between organizations' promotion rates and employees' performance. These findings contribute to the long-standing debate on the value of internal labor markets in sociology. Despite much theorizing, we have limited empirical evidence that strong internal promotion systems are associated with worker performance. The closest evidence comes from economics. Bertrand et al. (2020) show that in the Indian Administrative Service, older entrants who had limited promotion prospects were less effective and more likely to face disciplinary action, but a reform extending the retirement age reduced these performance gaps. Similarly, Bianchi et al. (2020) study an Italian pension reform and find that when older workers delayed retirement, younger colleagues experienced slower wage growth and fewer promotions—evidence of blocked career ladders within firms. Our study differs by moving beyond institutional settings and single-firm data to construct organizational-level measures of internal and external promotion rates across thousands of firms.

Another related line of work is in management, such as Bidwell's (2011) study of a large U.S. financial services firm. He shows that external hires are initially paid more and have stronger observable qualifications, yet they perform worse and leave more often than workers promoted internally. That line of work focuses on comparing outcomes for individuals who enter jobs through external hiring versus internal promotion. Our study, by contrast, shifts attention from those individual movers to the broader workforce, asking how an organization's overall reliance on internal versus external hiring reverberates across incumbent employees.

The paper is structured as follows. Section 2 details the existing literature and explains our argument. Section 3 discusses how we assembled the LinkedIn-USPTO dataset and introduces our methodology. Section 4 presents the results and Section 5 concludes.

2. THE VALUE OF INTERNAL LABOR MARKETS

A central question in organizational sociology is whether variation in internal labor markets relates to employee performance and organizational outcomes. Classic theorists highlighted their motivational value. Weber ([1922] 1978) saw bureaucratic hierarchies and structured career ladders as essential for order and discipline in large organizations. March and Simon (1958) and Blau and Scott (1962) similarly emphasized how formal mobility systems aligned individual incentives with organizational goals. Doeringer and Piore (1971) argued that internal labor markets stabilized employment and encouraged the accumulation of firm-specific skills, thereby supporting higher productivity. Kalleberg (1977) added that when promotion opportunities were limited, morale and initiative suffered. Rosenbaum (1979) and Lazear and Rosen (1981) suggested that promotions work like tournaments, motivating employees through competition for advancement. From these perspectives, internal labor markets are valuable because they motivate effort and channel it into long-term organizational performance.

At the same time, other scholars pointed to their limitations. Edwards (1979) argued that rigid internal systems could dampen flexibility and reduce responsiveness to new challenges. Tolbert (1996) observed that many organizations turned increasingly to external hiring, reflecting a belief that fresh perspectives and new skills could raise performance in ways rigid internal ladders could not. This line of work suggests that reliance on external hiring can, under certain conditions, be more beneficial than cultivating talent solely from within.

Although this debate has shaped organizational sociology for decades, empirical evidence remains surprisingly limited. Most studies have focused on a narrower comparison: whether individuals promoted from within or hired from outside perform better once in the job. This interdisciplinary line of research has produced mixed findings. Oyer (2007) finds that externally recruited economists are more productive than those promoted internally, while Chan (2007) shows that external hires in a U.S. financial corporation exhibit better performance. In contrast, Bidwell (2011) finds that, despite higher education and experience, external hires tend to underperform internal promotions in their first two years and are more likely to leave the organization. Similarly, Groysberg et al. (2008) show that star stock analysts perform worse after moving to new firms, underscoring the importance of firm-specific skills, and Rollag et al. (2005) argue that internal hires experience greater productivity growth because of contextual learning.

Taken together, these studies illuminate the outcomes for workers who move into new jobs but leave open a broader issue raised by classical sociology: does the strength of a firm's internal labor market shape the performance of its existing employees? This question motivates our study. Before turning to the empirics, we discuss how hiring practices signal career opportunities and influence the motivation of the broader workforce.

2.1. Internal vs External Hiring as Signals

Many studies have shown that employees are highly concerned with career opportunities (e.g., Johnson and Mortimer 2011; Kalleberg and Marsden 2013; Bertrand et al.

2019). While canonical models emphasize pay as the central incentive, recent surveys of employee preference have consistently shown the importance of non-compensation-related job attributes including advancement opportunities. For example, the Wisconsin Longitudinal Survey asks respondents to rate the importance of 12 attributes when choosing a job. The most valuable attributes include promotional opportunities, doing interesting work, and job security, whereas pay and benefits are only ranked six and eight out of 12, respectively (Daw and Hardie 2012). Similarly, the General Social Surveys over the years have shown that advancement opportunities is almost as important to workers as income is (Kalleberg and Marsden 2013). Other surveys and experiments show similar patterns, with respondents valuing advancement opportunities just as much as pay (Gallie, Felstead, and Green 2012; Johnson and Mortimer 2011).

Organizations' hiring strategies can shape how employees view their chances for advancement. It is often difficult for workers to know their actual likelihood of promotion. One way they gauge opportunities is by watching their peers. Both internal promotions and external hires are highly visible and often the subject of workplace gossip and conversation. When many vacancies are filled by colleagues, employees may see a stronger career ladder within the organization and believe their employer values loyalty and development. In contrast, when most vacancies go to external hires, employees may become disillusioned about their chances for promotion and feel the organization is less committed to developing internal talent.

These signals matter because they can directly influence performance through two related pathways. First, career ladders act as incentives: just as financial rewards spur effort, the possibility of promotion encourages employees to invest more in their work. Second, the prospect of advancement fosters longer-term commitment. Employees who see viable internal career paths are more likely to deepen firm-specific skills and build stronger relationships with coworkers—investments that are critical for productivity (Groysberg et al. 2008; Bidwell and Keller 2014). Taken together, these pathways suggest that internal promotion opportunities not only signal career prospects but also translate those signals into higher employee performance.

2.2. Boundary Condition: Time to Retirement

Our argument rests on the idea that employees care about their advancement opportunities, but this concern is not uniform across all workers. Those nearing retirement are less likely to be motivated by the prospect of future promotions, since they have limited time left to climb the career ladder. With only a few years remaining in their tenure, they may prioritize planning for life after work rather than seeking career growth within the firm. As a result, we expect an organization's reliance on internal versus external hiring to have little influence on the performance of employees close to retirement.

2.3. Strategic Context: Patent Inventors

We examine our proposition in the context of patent inventors, a setting that offers large-scale, longitudinal, and relatively standardized proxies for individual performance. In many settings, performance ratings are subjective and not comparable across organizations or industries. By contrast, inventors' output can be observed using patent counts and forward citations. This approach parallels work in domains with readily observable performance—such as athletes' on-field statistics (Zhang 2017, 2019), sell-side analysts' forecast accuracy (Kempf and Tsoutsoura 2021), and academics' citation impact. Unlike most such domains, the inventor setting spans a far larger number of organizations and years, enabling analysis at scale.

3. DATA AND METHOD

One contribution of this study is to use LinkedIn profiles to measure organizations' internal promotion and external hiring rates at the firm-year level. We detail how we construct these measures, then link them to inventors' USPTO patent records. The merged dataset allows us to examine how organizations' hiring practices relate to inventors' patent output.

3.1. LinkedIn Profiles

Researchers have used a variety of approaches to study internal labor markets. Early work relied heavily on surveys, either of workers or organizations, to capture promotion opportunities (e.g., Kalleberg 1977; Althauser & Kalleberg 1981; Pfeffer & Cohen 1984; Kalleberg & Marsden 2013; Gallie, Felstead, and Green 2012; Wilmers & Kimball 2021). While informative, such surveys are costly, often limited in scope, and typically reflect employees' subjective perceptions rather than firms' actual practices.

Other scholars have turned to case studies and personnel records from single firms, which often provide rich detail on promotions, pay, and mobility (Doeringer & Piore 1971; Baker, Gibbs & Holmström 1994; Bidwell 2011; Rosenbaum 1979; Lazear and Rosen 1981). Administrative and employer datasets have also been used in specific contexts, though they tend to be restricted to particular industries or countries (Althauser & Kalleberg 1981). While these approaches yield valuable insights into how internal labor markets operate, they are typically not generalizable beyond the specific organizations or settings under study.

More recently, scholars have exploited policy shocks to career ladders, such as pension reforms, to study the role of ILMs in shaping employee outcomes (Bertrand et al. 2020; Bianchi et al. 2020). Yet even these studies do not observe organizations' actual internal promotion rates.

The advent of public career platforms such as LinkedIn provides a unique opportunity to observe internal promotion and external hiring rates across a broad set of organizations. Unlike traditional surveys or single-firm personnel records, LinkedIn offers career data that span industries, occupations, and geographies, enabling researchers to construct comparable measures of mobility at scale. As one of the largest professional networking platforms, LinkedIn in 2024 hosts self-reported career histories for more than 200 million users in the US. These histories typically include job titles, employers, and employment dates, allowing us to identify both internal job changes within firms and external moves across firms. LinkedIn data are particularly informative for high-skill, white-collar occupations—such as engineers, scientists, and managers—where maintaining an online professional profile has become standard practice (Ge, Huang, & Png 2016; Raj et al. 2020).

At the same time, important limitations remain. Profiles are self-reported and may be incomplete or selectively updated, especially among workers in lower-skill occupations or older cohorts less likely to use digital career platforms. Coverage is therefore uneven across the labor market, with blue-collar and less digitally engaged groups underrepresented.

Nonetheless, validation studies indicate that LinkedIn-based measures align well with external benchmarks: Ge, Huang, and Png (2016) show close agreement between LinkedIn profiles and patent records for scientists and engineers; World Bank–LinkedIn (2018) and Gupta (2023) find that mobility and migration patterns inferred from LinkedIn align closely with administrative sources (e.g., UN/OECD/ILO statistics and USCIS PERM records); and Rock (2022), Tambe, Hitt & Brynjolfsson (2020), and Berry, Maloney & Neumark (2024) show that LinkedIn-derived firm-level measures—such as employee counts, occupational composition, and workforce demographics—correlate strongly with government surveys (e.g., BLS OEWS/ACS) and employer filings (e.g., Compustat, EEO-1).

In Appendix Section A, we perform our own evaluation of the LinkedIn data. We first compare the distribution of LinkedIn users with national statistics. We then evaluate the LinkedIn data against two benchmarks: the American Community Survey (ACS) at the industry–year level and the restricted Employer Information Report (EEO-1; Standard Form 100) at the firm–year level. We compare along both occupational and demographic dimensions and find that LinkedIn profiles largely track these nationally representative sources.

3.2. Measuring Internal/External Labor Markets

We identify both internal and external moves using LinkedIn career profiles. An internal promotion occurs when an individual moves from one job to another within the same organization, while an external hire is an instance where an individual moves from one employer to another. While we classify all internal transitions as promotions, some of these moves may represent lateral transfers. To address this concern, we adopt a stricter definition of promotion based on job seniority: for each job title in LinkedIn, we assign a seniority score using the median number of years it takes individuals to first reach that title (see Amornsiripanitch et al. 2022). We then define promotions as moves from a lower-seniority job to a higher-seniority job, which account for roughly 60 percent of internal transitions. Results remain substantively similar when applying this stricter definition.

Finally, because entry-level jobs cannot be filled by internal promotion, we exclude them from our calculations by restricting to jobs requiring at least three years of seniority. Using alternative thresholds produces consistent results.

From these job-to-job transitions, we construct organization-year measures of hiring practices. An organization's internal hiring rate is defined as the number of employees promoted within the organization in a given year divided by the total number of employees observed for that organization-year. We also calculate the external hiring rate, defined as the number of employees hired from outside the organization in a given year divided by the total number of employees in that organization-year. Together, these measures capture the extent to which organizations rely on internal promotions versus external hires when filling vacancies.

To assess our measure, we first compare it against external indicators of how employees perceive advancement opportunities within their organizations. Online review platforms offer a rare large-scale window into such perceptions. Glassdoor, for instance, asks employees to rate their employers on "career opportunities," while Indeed includes a dimension on "job security and advancement." Although these reviews are self-reported and subject to selection bias and uneven participation across industries, they remain one of the few scalable sources of comparable data on perceived career opportunities. Indeed's wording aligns particularly well with our construct, as it captures both promotion prospects and the broader sense of stability associated with internal labor markets (Zhang 2023). We therefore use Indeed's "job security and advancement" rating as an external benchmark.

As shown in Figure 2, organizations with higher internal hiring rates also tend to receive higher advancement ratings on Indeed (r = 0.15). Although the correlation is modest—unsurprising given differences in measurement and substantial noise—the positive relationship provides supportive evidence for the validity of our measure.

[Insert Figure 2 about here]

Second, we compare our measure to organizations' job posting. The intuition is that employers who rely more on internal labor markets will more fill mid-career or managerial positions internally, and thus post fewer of these roles publicly. Conversely, organizations that depend more on external hiring should advertise proportionally more mid- and senior-level positions. To approximate this distinction, we compute the ratio of non-managerial (entry- and early-career) postings to managerial (mid- and senior-level) postings for each organization-year using the near-universe of U.S. job postings from 2010 to 2023 provided by Lightcast. A higher ratio indicates relatively more entry-level hiring, consistent with greater reliance on promotion for filling higher-level jobs.

This ratio may also reflect structural features of an organization's hierarchy—such as the span of control or the number of managerial layers—rather than promotion practices per se. Nonetheless, it offers a scalable proxy that can be compared to our LinkedIn-based measure. As shown in Figure 3, organizations with higher internal hiring rates relative to external hiring rates on LinkedIn also tend to have higher ratios of non-managerial to managerial postings (r = 0.10). The association is again modest, but the consistency across two distinct external benchmarks provides additional confidence in the validity of our measure.

[Insert Figure 3 about here]

Finally, we evaluate the validity of our measure by benchmarking it directly against open administrative data. Specifically, New York City publishes annual citywide payroll data for all municipal employees, beginning with fiscal year 2014, as part of its NYC Open Data initiative (data.cityofnewyork.us). These data include employees' names, job titles, agency affiliations, salaries, and working hours for each fiscal year. Following the same procedure used to measure internal hiring rates in the LinkedIn data, we first identify internal hires by tracking job title changes within each agency. We then aggregate these individual cases of internal hiring at the city-government level for each year to calculate the annual internal hiring rate. Using LinkedIn data, we manually identify agencies affiliated with the New York City government and calculate the average internal hiring rate for each agency across years.

Figure 4 compares the temporal trends of LinkedIn-based internal hiring rates with those derived from NYC Open Data among workers employed by the NYC government. The two lines generally align. We observe small gaps that may reflect two measurement issues, in addition to possible selection concerns with LinkedIn data. First, NYC administrative data are organized by fiscal year, while LinkedIn records follow calendar years, and month information on LinkedIn is not always precise. Second, some users report their employer at the city-government level—for example, "City of New York," which accounts for the largest number of employees on LinkedIn—rather than specifying the agency where they work. This issue is likely less pronounced in corporate contexts. Nevertheless, the average difference between the two measures over time is about one percentage point. Overall, the close alignment suggests that our LinkedIn-based measure captures similar dynamics to the administrative benchmark.

[Insert Figure 4 about here]

3.3. USPTO Database

Building on these validations, we link our LinkedIn-based measures to patent data to examine how internal labor markets relate to employee innovation. We merge the LinkedIn database with the PatentsView platform, an open data project jointly developed by the U.S. Patent and Trademark Office, the American Institutes for Research, and the University of California, Berkeley. PatentsView provides comprehensive records of U.S. patents since 1976, including application and grant dates, technology classifications, and both backward and forward citations. The database also contains disambiguated information on inventors, applicants, assignees, and examiners, with each patent assigned a unique identifier that allows us to link inventor-level career information with patent outcomes.

The LinkedIn data add critical information that is missing from USPTO records. The USPTO lists the assignee on each patent application, who is often—but not necessarily—the inventor's employer at the time of filing. However, the USPTO provides no employment information for inventors in non-filing years. Since most inventors patent intermittently, USPTO data alone observe employers for only a fraction of careers. Prior work has addressed this gap by focusing on prolific inventors who patent nearly every year (e.g., Moretti 2021), but this excludes most inventors and limits the study of typical career paths. The USPTO also lacks job titles, which matter because position shapes access to resources, role expectations, and collaboration networks. By merging LinkedIn and USPTO records, we recover full career histories and titles, enabling a more comprehensive analysis of how firms' internal promotion practices are associated with inventors' innovative output.

3.4. LinkedIn-USPTO Matching

We constructed a crosswalk linking USPTO inventor records to professional profiles on LinkedIn for the period 2000–2025. The USPTO dataset, downloaded in 2025, contained 4,154,433 inventors. We restricted the sample to 1,464,870 U.S.-based inventors with at least one granted patent since 2000.

To identify their LinkedIn profiles, we used a multi-step matching strategy combining exact and fuzzy approaches. We first applied exact matches on inventors' names, employers, and years of activity to capture straightforward cases. For the remainder, we implemented a fuzzy matching procedure. Using a text embedding model, we converted names and employer information into vectors, computed cosine similarity scores between potential matches, and retained pairs with similarity scores of 0.95 or higher. We then used OpenAI's 4o model to systematically review and validate these high-scoring pairs.

This procedure yielded 446,058 matched LinkedIn profiles. Additional technical details of the matching process are provided in Appendix Section B. Our matched sample reflects somewhat higher inventor quality than the full USPTO dataset. The average inventor in the matched sample has 1.83 granted patents, compared to 1.67 in the full sample. At the top end, the 90th percentile inventor in the matched sample has 26 patents, versus 15 in the full sample. In both datasets, the most common technology section (based on the Cooperative Patent Classification, CPC) is physics, representing 34 percent of the matched sample and 29 percent of the full sample. Gender representation differs slightly: women account for 8.32 percent of inventors in the matched sample compared to 10.31 percent in the full sample. Figures A.1 and B.1 provide additional comparisons between matched and unmatched inventors as well as between our LinkedIn sample and national-level statistics.

3.5. Dependent Variables: Employee Innovation

We use an inventor's adjusted three-year forward citations on the granted patents as the dependent variable. This citation count, calculated at an individual-firm-year level, counts the number of times that the inventor's patents submitted that year are cited within the three years of their grant. Our measure is time-varying, such that the patent is counted for the year in which it was initially submitted. For example, if an inventor submitted two patents in 2018, then the number of patents produced in that year is two, even though these two patents may be officially approved years later. Her three-year citation rate is the number of patents that cite these two patents within three years after the patents' approval dates (Hall, Jaffe, and Trajtenberg 2001).

Forward citation count could indicate both the quantity and the quality of innovation, as it is dependent on both the number of patents granted and the number of times they are cited. Citation rates tend to vary significantly across technology classes and over time, so we adjusted each patent's three-year citation count by the mean citation count in that class-year (Hall, Jaffe, and Trajtenberg 2001). Because the adjusted three-year forward citation rate has a mean value below one, we add 0.01 to it before taking the natural logarithm. We re-estimate our main model using inverse hyperbolic sine, and modified log transformation suggested by Chen and Roth (2024).[1] In addition, to address potential truncation issues

[1] Chen and Roth propose a "modified logarithm" transformation that better handles zero values. The transformation is defined as m(y) = ln(y) if y is greater than 0, and m(y) = -x if y is equal to 0. Following their recommendation, we set x = 3 in our analysis. This choice implies that the shift from zero to a positive

(i.e., patents submitted in 2024 and 2025 not having a full three-year window to receive citations), we re-estimate our main model excluding years beyond 2023. All results remain robust.

3.6. Alternative Measures of Employee Innovation

Besides our main dependent variable, we also present results on five alternative measures of patent output (see Table E.1 for more details). First, we count the number of patent applications filed by each inventor in each year of employment, regardless of whether they were granted or not. This measure does not distinguish successful patents from unsuccessful ones, thus measuring only the productivity of each inventor without considering the quality of their patents.

Second, we use the logged number of patents. This measure, similar to the forward citation count, is calculated based on patents' initial submission dates. It does not include patents that were later denied by the patent office; approximately half of the patents submitted were eventually granted.

Third, we measure the economic importance of innovations produced by each inventor in each firm in each year. This measure, developed by Kogan et al. (2017), tracks the stock market's reaction to news about individual patents. Specifically, following each patent's grant, they compute the firm's abnormal stock return over a three-day window surrounding the grant date. We measure each inventor's annual patent value at an assignee by summing the values of their patents granted that year.

Our fourth alternative measure accounts for coauthor numbers in citation counts. Some patents are authored by only one or two inventors, and some are by a large team of inventors. Arguably the larger the coauthor team, the less credit should be attributed to each inventor. For this alternative measure, we simply divide the citations by the number of coauthors on the patent.

Finally, we show results using the logged unadjusted three-year forward citation

citation count (i.e., the extensive margin) is treated as equivalent to a 100 log-point increase on the intensive margin—comparable to a change from ln(a) to ln(b) where ln(b) - ln(a) = 1.

counts. This measure differs from our main citation measure in that it does not account for different citation rates across technology classes. For these alternative dependent variables except coauthor-adjusted ones, we add one to the original values before taking the natural logarithm. For coauthor-adjusted patent and citation counts, we add 0.01 to the original values since their means are significantly below one.

3.7. Independent Variables: Internal Hiring Rates

For our main analyses, we construct an organization-year internal hiring rate based only on inventors in the LinkedIn–USPTO matched sample. This measure equals the number of inventors promoted within the organization in a given year divided by the total number of inventors observed that year, excluding the focal inventor so that it captures the promotion rates among peers. We also compute an external hiring rate, defined analogously as the share of inventors newly hired from outside the organization.

Focusing on inventors rather than the broader workforce ensures that our measure reflects the career ladders most salient to R&D employees. As before, we exclude entry-level roles with fewer than three years of seniority. Results are robust to alternative thresholds as well as to a stricter, seniority-based definition of promotion (Amornsiripanitch et al. 2022).

3.8. Control Variables

We include several time-varying organization-level controls to account for potential confounders: the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. These variables capture differences in organization size, R&D intensity, employee turnover, managerial hierarchy, and innovative capacity—factors shown to be associated with employee innovation (Argyres, Rios, and Silverman 2020; Acs and Audretsch 1988; Akcigit and Goldschlag 2023).

We construct these measures primarily from LinkedIn data. The number of professional employees is the logged count of LinkedIn profiles linked to a firm in a given year. Managers and R&D staff are identified using self-reported job titles, which we aggregate to compute the annual share of employees with managerial or R&D roles. Average employee tenure is calculated by summing the number of years each worker has been employed at the organization up to a given year and dividing by the number of employees in that firm-year. To measure cumulative patenting, we use PatentsView data and count the total number of patents granted to each organization up to, but not including, the focal year.

3.9. Analytical Strategy

To examine the relationship between internal hiring rates and inventors' innovative output, we estimate models with multiple fixed effects. These specifications account for unobserved heterogeneity at the inventor, job, organization, and time level. Although our approach does not provide causal identification, it systematically documents associations between promotion practices and employee performance and offers a first step toward understanding these dynamics. Our analyses are conducted at the inventor–year level, and we implement three sets of fixed effects.

Our baseline model uses inventor–title fixed effects, which capture variation both from inventors moving across organizations and from changes in hiring rates within the same organization over time. A key endogeneity concern is that an inventor's innovative output and her future advancement opportunities may both be influenced by job title changes as she advances in her career. By including inventor–title dyadic fixed effects, we track changes within the same inventor while holding the job title constant. Job titles are drawn from inventors' self-reported LinkedIn profiles, which are typically more precise and detailed than standard occupation codes.

Second, to account for unobserved firm-level and geographic confounders, we extend this model to include firm–location fixed effects alongside inventor–title fixed effects. This specification follows inventors within the same job title while holding constant any time-invariant characteristics specific to a firm in a given state.

Finally, we adopt an even stricter specification that incorporates inventor–title–employer–location dyadic fixed effects, rather than including inventor–title and employer–location separately.

This approach helps control for time-invariant inventor–employer match quality, leaving identification to rely on within-inventor, within-firm changes across time.

All three models can be summarized by the following specification:

$$Y_{ift} = \beta_1 \cdot IPR_{ft} + \beta_3 \cdot X_{ft} + Year_t + WY_{it} + JT_{it} + IT_{ij} + u_{ift}, \tag{1}$$

where Y_{ift} is the log of inventor i's innovation output in year t while working for firm f. IPR_{ft} is the number of inventors promoted internally divided by the total number of inventors in firm f in year t, excluding the focal inventor. X_{ft} denotes time-varying firm-level control variables. $Year_t$, WY_{it}, and JT_{it} are fixed effects for calendar year, an inventor's cumulative years in the workforce, and years in the current job, respectively. IT_{ij} are inventor–title fixed effects in our baseline model. We replace these with stricter fixed effects, as described above, in subsequent specifications. In Table 1, we regress Y_{ift} on both internal promotion and external hiring rates. As noted, external hiring rates are calculated as the number of external hires divided by the total number of inventors in firm f in year t, excluding the focal inventor. All analyses are estimated using ordinary least squares (OLS) with standard errors clustered at the firm level.

4. RESULTS

We present the results in four parts. First, we show that organizations with higher internal promotion rates among inventors are also associated with higher levels of innovative output. Second, we examine age as a moderator and find that the association is concentrated among mid- and early-career inventors, with little or no relationship for those nearing retirement. Third, we conduct a series of robustness checks to assess the stability of our findings. Finally, we compare internally promoted and externally hired inventors, finding that the former are associated with stronger innovation outcomes.

4.1. Main Estimates: Internal Hiring Rates and Inventor Performance

We first explore the link between a firm's internal hiring rates and its inventors' productivity. In Table 1, the first three models predict inventors' adjusted three-year citation counts using the internal hiring rate. Going from left to right, we add an increasingly stricter model specification. Model 1 uses inventor-title fixed effects; Model 2 includes fixed effects on inventor-title and employer-location seperately; and Model 3 include inventor-title-employer-location dyadic fixed effects.

Across all models, we find a positive association between a firm's internal hiring rate and an inventor's citation counts. In Model 1 of Table 1, which includes inventor–title fixed effects, a one–standard deviation higher internal hiring rate is associated with about 1.8 percent more adjusted three-year forward citations. When employer–location fixed effects are added in Model 2, the association decreases to 1.1 percent but remains economically meaningful. These models compare the same inventor across different organizational contexts, so the variation reflects both differences across firms and changes within firms over time.

Model 3 applies the strictest specification, incorporating inventor–title–employer–location fixed effects. Even under this stringent setup, we continue to observe a positive association: a one–standard deviation increase in internal hiring rates is linked to about a 1.1 percent increase in three-year citation counts. The association is not uniform, however, and appears strongest among star inventors and in firms with larger inventor populations. As shown in Appendix Section H, a one–standard deviation increase in internal hiring rates corresponds to a 2.0–3.4 percent increase in citation counts among star inventors. The pattern is also more pronounced in larger organizations: while our baseline sample requires at least five inventors per firm, the estimated effect rises to 1.6–3.5 percent when using thresholds of 10 or 20 inventors.

In Models 4, 5, and 6, we add an additional independent variable: the number of external hires relative to the number of inventors, which is generally negatively associated with inventors' productivity. External hiring can be interpreted as reducing opportunities for internal promotion, since filling these positions internally would have raised the internal hiring rate. In this sense, higher external hiring is typically associated with lower internal promotion, reflecting a trade-off in how organizations fill vacancies.

[Insert Table 1 about here]

4.2. Moderator: Breaking Down by Cohorts

We now turn to a boundary condition. Figure 5 plots the interaction between inventors' age and internal hiring rates from Table 1. The association between an organization's internal hiring rates and inventors' productivity is expected to weaken for those closer to retirement, since advancement opportunities matter less late in a career. The results align with this expectation: the positive association is concentrated among mid- and early-career inventors, while it is minimal for those nearing retirement. Specifically, for inventors aged 22 to 40, a one–standard deviation higher internal hiring rate is associated with 1.0–3.0 percent more citations, depending on the model specification. By contrast, for later-career inventors the association is close to zero and not statistically significant.

[Insert Figure 5 about here]

In addition to examining age cohorts, we also consider inventors who have reached the highest occupational rank within their organizations. Once at the top, these individuals are likely less influenced by internal career ladders, as opportunities for further advancement are limited. While those in senior positions are typically older, Appendix Section I shows that the association between internal promotion rates and performance remains notably weaker for inventors in the most senior roles, even after controlling for their age.

4.3. Robustness Checks

We conduct several additional analyses to assess the robustness of our results. First, instead of relying only on current internal promotion rates, we consider historical measures. Because the patenting process can span anywhere from several weeks to several years, we calculate an organization's internal hiring rate using a three-year rolling window to account for potential lags between hiring and observed innovation outcomes. The results, reported in Table D.2, are consistent with our main models.

Second, we reconstruct our measure of internal promotion by applying a stricter seniority criterion. In our sample, about 60 percent of internal moves involve a shift from a lower- to a higher-seniority position. Our baseline measure includes all internal transitions, regardless of seniority change. To test robustness, we restrict the measure to include only moves that result in higher-seniority positions. As shown in Table D.1, the results remain consistent with our main analyses.

Third, we employ five alternative measures of innovation output, including the number of patent applications (granted and ungranted), patents' economic values, citation counts adjusted for team size, and logged counts of patents and three-year forward citations without adjustment. The results, presented in Table E.1, align with our primary findings.

Fourth, we test the sensitivity of our results to different sample thresholds. Our baseline analysis requires at least five inventors per firm-year (Table 1). In Appendix Section F, we replicate the analysis using higher thresholds and observe consistent patterns.

Fifth, we examine whether inventors' prior productivity is related to their moves into firms with different promotion environments. Specifically, we compare inventors who began at the same firm but later moved to firms with internal promotion rates at least 10 percentage points higher versus lower. As shown in Appendix Section G, we find no significant differences in their performance prior to the move.

Finally, in Appendix Section H, we address potential selection concerns related to our matched sample, which skews toward more successful and male inventors. Using a split-sample approach, we show that the observed associations also hold among women and non-top inventors, whose performance patterns more closely resemble those of unmatched inventors.

4.4. Performance of Newly Promoted/Hired Inventors

To assess the broader performance patterns of internal versus external hiring, we also compare the outcomes of inventors who were promoted within their organizations to those who were hired from outside. Table J.1 classifies all inventors into these two groups, based on how they entered their current position, and compares their performance during the first five years in the role. On average, internally promoted inventors record around 12 percent more citations than externally hired inventors with the same job title and workforce tenure at the same firm. Figure J.2 illustrates how this gap evolves over time. In the first two years, internally promoted inventors show citation counts on average more than 20 percent higher than those of external hires. The difference narrows beginning in the third year, and by the fifth year the two groups exhibit similar performance levels. The initial advantage of internal inventors likely reflects their greater familiarity with firm-specific skills and routines when starting the new role.

Figure J.1a uses individual fixed effects to track changes in an inventor's productivity before and after an internal promotion. Inventors show steady increases in productivity leading up to promotion and then maintain similar levels afterward. This pattern is consistent with the idea that promotion opportunities are linked to improvements in performance.

Figure J.1b also uses individual fixed effects to examine changes in inventors' productivity before and after switching employers. Productivity tends to decline in the period leading up to departure and falls further immediately after joining a new organization. Within three years, however, inventors return to roughly their pre-switch productivity levels. This post-move dip aligns with Groysberg et al. (2008), who document that newcomers often require time to acquire firm-specific skills and adapt to a new organizational environment.

5. DISCUSSION AND CONCLUSION

This paper uses LinkedIn profiles to measure organizations' internal labor markets at scale. By merging LinkedIn profiles with USPTO patent data, we show that organizations with stronger internal labor markets are associated with higher inventor productivity—though this pattern does not hold for inventors nearing retirement.

These findings contribute to our understanding of the value of internal labor markets. Strong internal labor markets are often seen as signaling clearer promotion opportunities and supporting employee motivation. Although sociologists have long emphasized this point, empirical tools to measure internal labor markets and assess their significance have been limited. Much of the management literature has instead compared the performance of internally promoted and externally hired individuals. Such analyses, however, leave open the broader question of whether the overall strength of an organization's internal labor market is associated with the performance of its broader workforce.

Organizations often turn to external labor markets to meet the challenges of growing task complexity and fast-changing demands. External hiring is seen as a way to access diverse skills and maintain flexibility, while internal labor markets are sometimes criticized as rigid or overly tied to seniority. Although many sociologists have emphasized the decline of internal labor markets, systematic evidence on whether they are linked to organizational performance remains limited. From a managerial perspective, external hiring is frequently assumed to provide greater benefits.

Our findings suggest that this assumption may overlook important dynamics. We find that internally promoted inventors tend to outperform their externally hired counterparts, and that organizations with greater use of internal labor market (i.e. higher internal promotion rates) also exhibit higher levels of performance among other inventors. These patterns point to a potential business case for maintaining robust internal labor markets, not only for staffing vacancies but also for shaping the broader performance environment within organizations.

5.1. Limitations

We highlight two major limitations of this study. First, LinkedIn profiles have inherent constraints. Unlike administrative records, LinkedIn profiles are self-reported and thus subject to selection bias. For instance, the sample may be skewed toward workers who rely more on external hiring, since individuals often have stronger incentives to create or update profiles when they are seeking outside opportunities. This selection dynamic could influence the observed patterns in our data. For example, as shown in Figure B.1, inventors successfully matched to LinkedIn profiles tend to be more productive, on average, than those who could not be matched.

Second, this paper does not employ a identification strategy. The main endogeneity concern is that an organization's internal hiring rate may be correlated with unobserved aspects of its work environment. While our use of fixed effects and a range of additional analyses helps to rule out some straightforward alternative explanations, these strategies cannot fully address the possibility of omitted variable bias. As a result, we refrain from making causal claims and interpret our findings as descriptive evidence of systematic associations.

What is the value of internal labor markets? From Max Weber in the early 20th century to Arne Kalleberg in more recent decades, sociologists have been intrigued by this question. Today, the advent of user-generated datasets offers unprecedented opportunities to revisit this and other classical questions in sociology. Using such data, we show that even in an era of flexible hiring, the strength of internal labor markets still matters for both workers and organizations.

REFERENCE:

Acs, Zoltan J., and David B. Audretsch. 1988. "Innovation in Large and Small Firms: An Empirical Analysis." *American Economic Review* 78 (4): 678–90. http://www.jstor.org/stable/1811167.

Agrawal, Anup, Charles R. Knoeber, and Theofanis Tsoulouhas. 2006. "Are Outsiders Handicapped in CEO Successions?" *Journal of Corporate Finance* 12: 619-644.

Akcigit, Ufuk, and Nathan Goldschlag. 2023. "Measuring the Characteristics and Employment Dynamics of U.S. Inventors." NBER Working Paper Series. https://www.nber.org/papers/w31086

Althauser, Robert P., Arne L. Kalleberg. 1981. "Firms, Occupations, and the Structure of Labor Markets: A Conceptual Analysis." In Ivar E. Berg (Ed.), *Sociological Perspectives on Labor Markets* (pp. 119 149). New York: Academic Press.

Amornsiripanitch, Natee, Paul A. Gompers, George Hu, Will Levinson, Vladimir Mukharlyamov. 2022. "Failing Just Fine: Assessing Careers of Venture Capital Backed Entrepreneurs Via a Non Wage Measure." (NBER Working Paper No. 30179). Cambridge, MA: National Bureau of Economic Research.

Argyres, Nicholas, Luis A. Rios, and Brian S. Silverman. 2020. "Organizational Change and the Dynamics of Innovation: Formal R&D Structure and Intrafirm Inventor Networks." *Strategic Management Journal* 41 (11): 2015–49. https://doi.org/10.1002/smj.3217.

Baker, George, Michael Gibbs, & Bengt Holmström. 1994. "The Internal Economics of the Firm: Evidence from Personnel Data." *Quarterly Journal of Economics* 109(4): 881 919.

Bayo-Moriones, Alberto, and Pedro Ortín-ángel. 2006. "Internal Promotion Versus External Recruitment in Industrial Plants in Spain." *Industrial and Labor Relations Review* 59 (3): 451-470.

Bertheau, Antoine. 2021. "Employer Search Behavior: Reasons for Internal Hiring." *Labour Economics* 73.

Bertrand, Marianne, Robin Burgess, Arunish Chawla, and Guo Xu. 2020. "The Glittering Prizes: Career Incentives and Bureaucrat Performance." *The Review of Economic Studies*, May, rdz029. https://doi.org/10.1093/restud/rdz029.

Berry, Alexander, Elizabeth M. Maloney, David Neumark. 2024. "The Missing Link? Using LinkedIn Data to Measure Race, Ethnic, and Gender Differences in Employment Outcomes at Individual Companies" (NBER Working Paper No.w32294). National Bureau of Economic Research.

Bidwell, Matthew. 2011. "Paying More to Get Less: The Effects of External Hiring versus Internal Mobility." *Administrative Science Quarterly* 56 (3): 369–407. https://doi.org/10.1177/0001839211433562.

Bidwell, Matthew, and Jr Keller. 2014. "Within or Without? How Firms Combine Internal and External Labor Markets to Fill Jobs." *Academy of Management Journal* 57 (4): 1035–55. https://doi.org/10.5465/amj.2012.0119.

Bidwell, Matthew, and Ethan Mollick. 2015. "Shifts and Ladders: Comparing the Role of Internal and External Mobility in Managerial Careers." *Organization Science* 26(6): 1629-1645.

Bianchi, Nicola, Giulia Bovini, Jin Li, Matteo Paradisi, Michael L. Powell. (2021). "Career Spillovers in Internal Labor Markets" (NBER Working Paper No. 28605). National Bureau of Economic Research.

Blau, Peter M., & Scott, W. Richard. (1962). *Formal Organizations: A Comparative Approach*. San Francisco: Chandler.

Chan, William. 2006. "EXTERNAL RECRUITMENT AND INTRAFIRM MOBILITY." *Economic Inquiry* 44 (1): 169–84. https://doi.org/10.1093/ei/cbj009.

Chang, M. H. 2023. "Cascading innovation: R&D team design and performance implications of mobility." *Strategic Management Journal*, 44(5), 1218–1253.

Chen, Jiafeng, Jonathan Roth. 2024." Logs with Zeros? Some Problems and Solutions." *The Quarterly Journal of Economics*, 139(2), 891–936.

Daw, Jonathan, and Jessica Halliday Hardie. 2012a. "Compensating Differentials, Labor Market Segmentation, and Wage Inequality." *Social Science Research* 41 (5): 1179–97. https://doi.org/10.1016/j.ssresearch.2012.05.009.

DeVaro, Jed, Antti Kauhanen, and Nelli Valmari. 2019. "Internal and External Hiring". *ILR Reviews* 72 (4): 981-1008.

Devaro, Jed, and Hodaka Morita. 2013. "Internal Promotion and External Recruitment: A Theoretical and Empirical Analysis." *Journal of Labor Economics* 31 (2): 227-269.

Dlugos, Kathryn, and JR Keller. 2021. "Turned Down and Taking Off? Rejection and Turnover in Internal Labor Markets." *Academy of Management Journal* 64 (1): 63-85.

Doeringer, Peter B., and Michael J. Piore. 1971. *Internal Labor Markets and Manpower Analysis*. Lexington, MA: Heath Lexington Books.

Duflo, Esther, Rema Hanna, and Stephen P Ryan. 2012. "Incentives Work: Getting Teachers to Come to School." *American Economic Review* 102 (4): 1241–78. https://doi.org/10.1257/aer.102.4.1241.

Edwards, Richard C. 1979. *Contested Terrain: The Transformation of the Workplace in the Twentieth Century*. New York: Basic Books.

Gallie, Duncan, Alan Felstead, and Francis Green. 2012a. "Job Preferences and the Intrinsic Quality of Work: The Changing Attitudes of British Employees 1992–2006." *Work, Employment and Society* 26 (5): 806–21. https://doi.org/10.1177/0950017012451633.

Ge, Chunmian, Ke-Wei Huang, and Ivan P. L. Png. 2016. "Engineer/Scientist Careers: Patents, Online Profiles, and Misclassification Bias." *Strategic Management Journal* 37 (1): 232–53. https://doi.org/10.1002/smj.2460.

Groysberg, Boris, Linda-Eling Lee, and Ashish Nanda. 2008. "Can They Take It With Them? The Portability of Star Knowledge Workers' Performance." *Management Science* 54 (7): 1213–30. https://doi.org/10.1287/mnsc.1070.0809.

Gupta, Abhinav. 2023. "Labor Mobility, Entrepreneurship, and Firm Monopsony: Evidence from Immigration Wait Lines." SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract$_i d =$ 4450105

Hall, H. Bronwyn, Adam B. Jaffe, and Manuel Trajtenberg. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools" NBER Working Paper Series. http://www.nber.org/papers/w8498. Hollister M. 2011. Employment stability in

the U.S. labor market: rhetoric versus reality. *Annual Review of Sociology* 37(1):305–24

Johnson, M. K., and J. T. Mortimer. 2011. "Origins and Outcomes of Judgments about Work." *Social Forces* 89 (4): 1239–60. https://doi.org/10.1093/sf/89.4.1239.

Kalleberg, Arne L. 1977. "Work Values and Job Rewards: A Theory of Job Satisfaction." *American Sociological Review* 42 (1): 124. https://doi.org/10.2307/2117735.

Kalleberg, Arne L., and Peter V. Marsden. 2013. "Changing Work Values in the United States, 1973–2006." *Social Science Research* 42 (2): 255–70. https://doi.org/10.1016/j.ssresearch.2012.09.012.

Keller, JR. 2018. "Posting and Slotting: How Hiring Processes Shape the Quality of Hire and Compensation in Internal Labor Markets." *Administrative Science Quarterly* 63 (4): 848-878.

Keller, JR, Kathryn Dlugos. 2023. "Advance 'Em to Attract' Em: How Promotions Influence Applications in Internal Talent Markets." *Academy of Management Journal*.

Kempf, Elisabeth, and Margarita Tsoutsoura. 2021. "Partisan Professionals: Evidence from Credit Rating Analysts." *The Journal of Finance* 76 (6): 2805–56. https://doi.org/10.1111/jofi.13083.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *Quarterly Journal of Economics* 132 (2): 665–712.

Lazear, Edward P., and Sherwin Rosen. 1981. "Rank-Order Tournaments as Optimum Labor Contracts." *Journal of Political Economy* 89 (5): 841-864.

March, James G., & Simon, Herbert A. (1958). *Organizations*. New York: John Wiley & Sons.

Moretti, Enrico. 2021. "The Effect of High-Tech Clusters on the Productivity of Top Inventors." *American Economic Review* 111 (10): 3328–75. https://doi.org/10.1257/aer.20191277.

Oyer, Paul. 2007. "Is There an Insider Advantage in Getting Tenure?" *American Economic Review* 97 (2): 501–5. https://doi.org/10.1257/aer.97.2.501.

Pfeffer, Jeffrey, Yinon Cohen. 1984. "Determinants of Internal Labor Markets in Organizations." *Administrative Science Quarterly*, 29(4), 550–572.

Rock, Daniel. 2022. "Engineering value: The returns to technological talent and investments in artificial intelligence." Brookings Institution.

Rollag, K., S. Parise, R. Cross, R. 2005. "Getting new hires up to speed quickly: The key to making new employees productive quickly, known as 'rapid on-boarding,' is to help them immediately build an informational network with co-workers." *MIT Sloan Management Review*, 46(2) Rosenbaum, James E. 1979. "Tournament Mobility: Career Patterns in a

Corporation." *Administrative Science Quarterly* 24, no. 2: 220–242

Tambe, Prasanna, Lorin Hitt, Daniel Rock, Erik Brynjolfsson. (2020). "Digital Capital and Superstar Firms" (NBER Working Paper No. 28285). National Bureau of Economic Research

Tolbert, P. S. 1996. Occupations, organizations and boundaryless careers.M. B. Arthur, D. M. Rousseau, eds. The Boundaryless Career: A New Employment Principle for a New Organizational Career. OxfordUniversity Press, Oxford, UK, 331–349.

Wang, Simeng, Yoon Jae Shin, and Letian Zhang. 2025. "Organizational Diversity Database: An Open Dataset on Firm Racial and Gender Composition."

Weber, Max. 2019. *Economy and Society: A New Translation* (Keith Tribe, ed. & transl.). Cambridge, MA: Harvard University Press.

Wilmers Nathan, Kimball William. 2021. "How Internal Hiring Affects Occupational Stratification." *Social Forces* (https://doi.org/10.1093/sf/soab131).

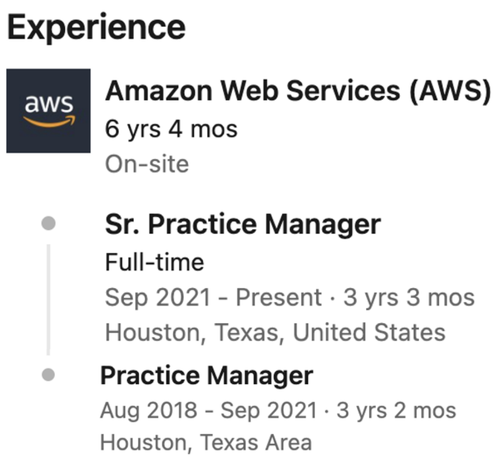
World Bank Group & LinkedIn. 2018. "Jobs, Skills and Migration Trends: Methodology & Validation Results." World Bank.

Zhang, Letian. 2017. "A Fair Game? Racial Bias and Repeated Interaction between NBA Coaches and Players." *Administrative Science Quarterly* 62(1): 1–23.

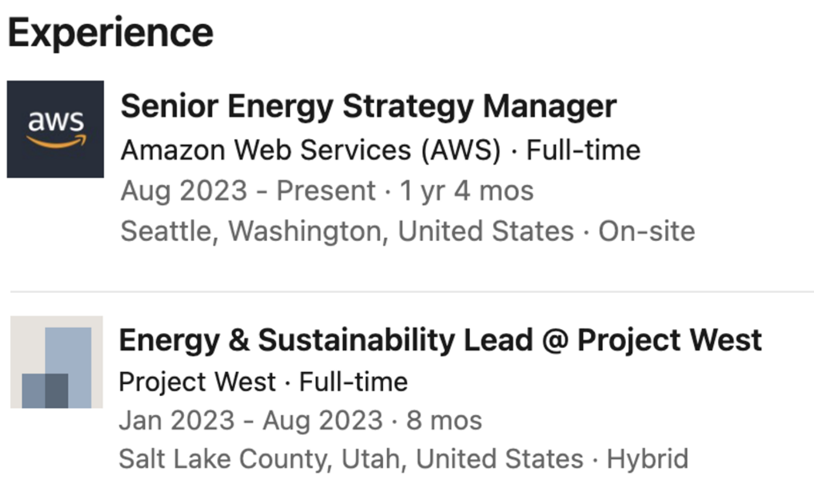
Zhang, Letian. 2019. "Who Loses When a Team Wins? Better Performance Isn't Always Better". *Organization Science*, 30(3).

Zhang, Letian. 2023. "Racial Inequality in Work Environments." *American Sociological Review*: 88(2) 252–283.

FIGURES AND TABLES



(a) Job title changes within the same employer



(b) Employer name changes

Figure 1: Identifying Internal hires and External Hires

Notes: These two graphs provide examples from LinkedIn profiles to illustrate how we identify internal promotions and external hires. The first graph shows a job title change within the same employer, which we classify as a promotion. The second graph shows a change in employer name, which we classify as an external hire.

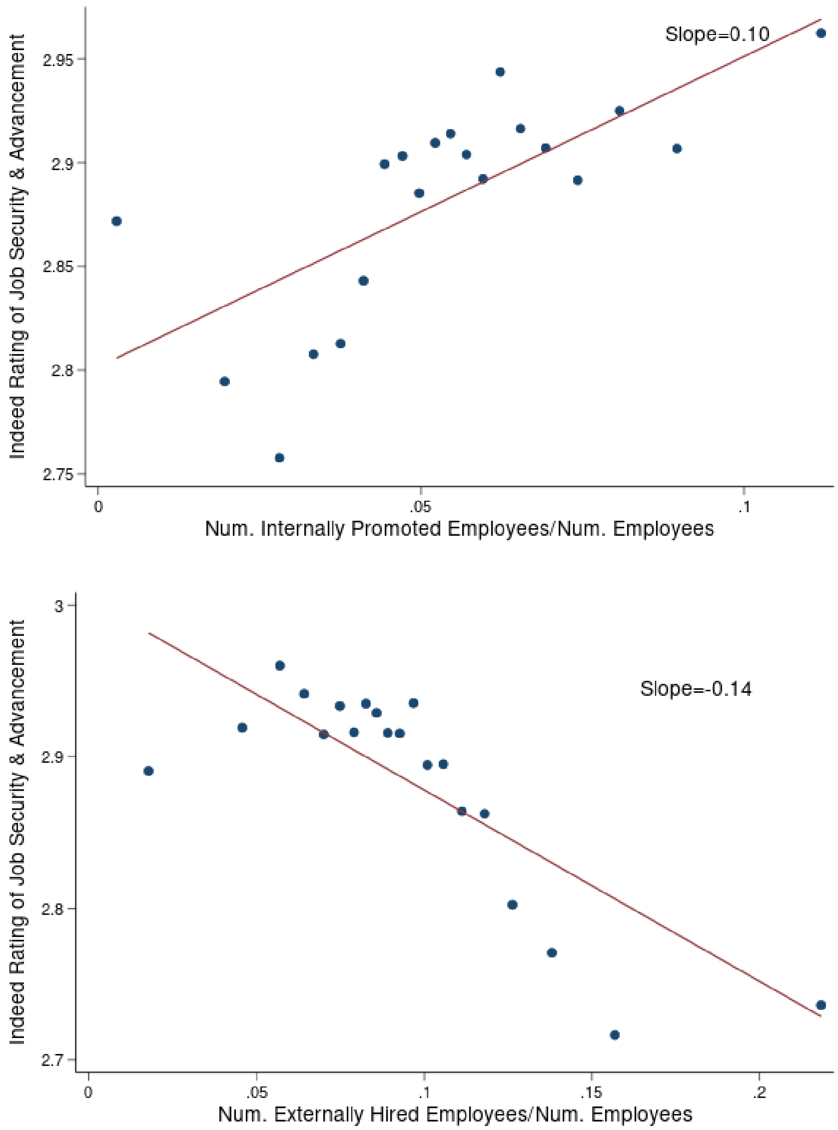


Figure 2: Comparison of Our Measure with Employee Reviews (Indeed)

Notes: These graphs show the descriptive association between a firm's internal (external) hiring rates and its employee ratings for job security and advancement, using data from Indeed. The analysis is based on our LinkedIn sample matched to Indeed reviews at the firm-year level. All data is presented in 20 equal-sized quantile bins according to the x-axis variable.

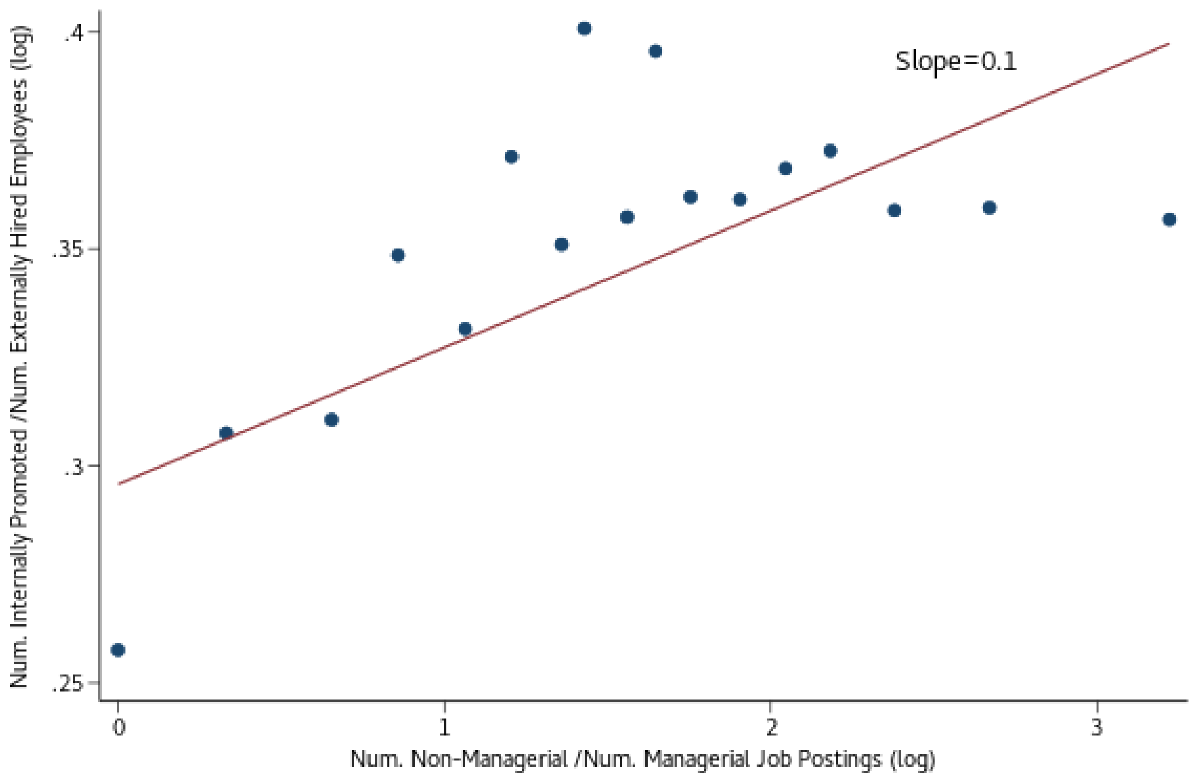


Figure 3: Comparison of Our Measure with Job Postings (Lightcast)

Notes: These graphs show the descriptive relationship between a firm's ratio of internal promotions to external hires and its ratio of non-managerial to managerial job postings, using Lightcast data. The analysis draws on our LinkedIn sample matched to Lightcast job postings at the firm-year level. All data are grouped into 20 equal-sized quantile bins based on the x-axis variable.

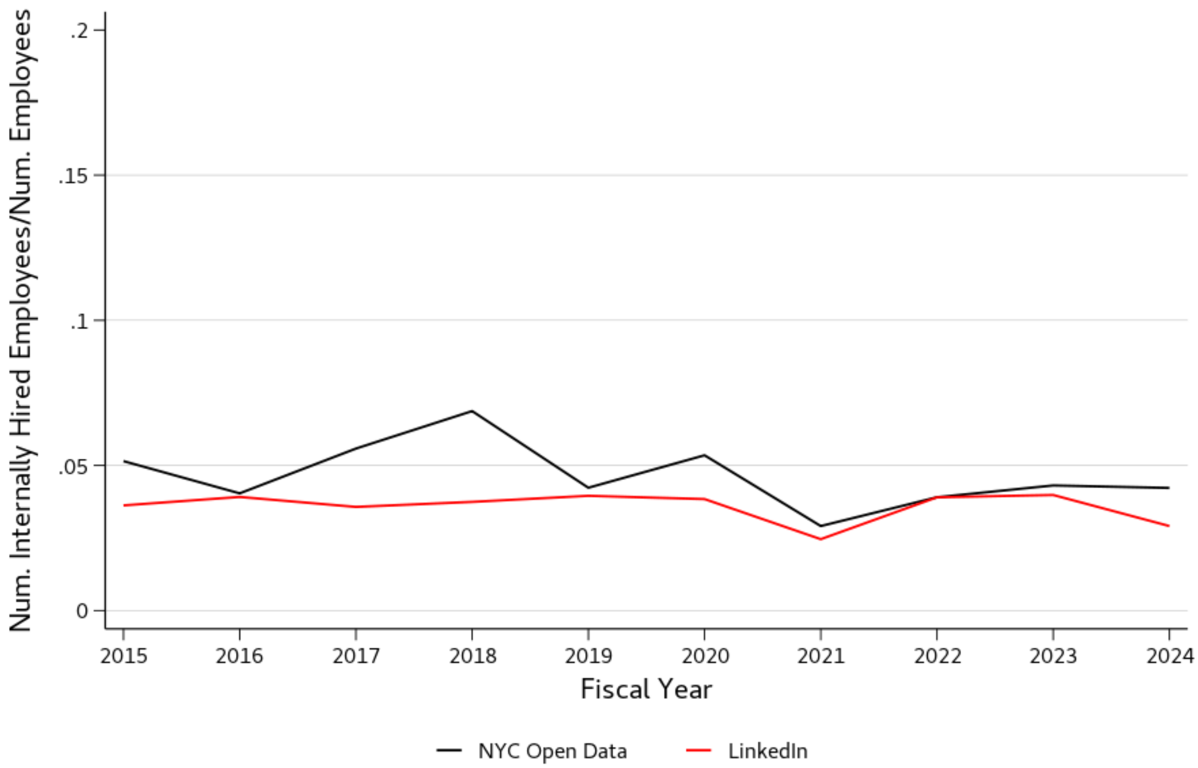
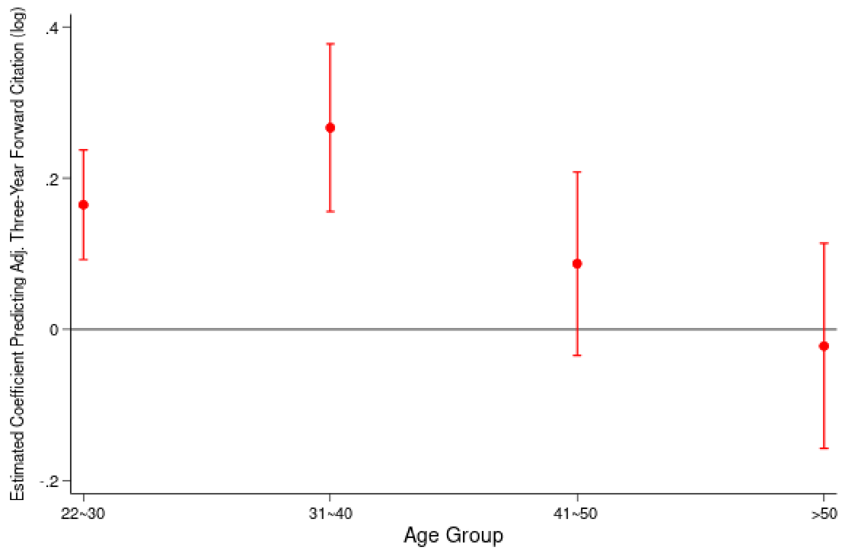
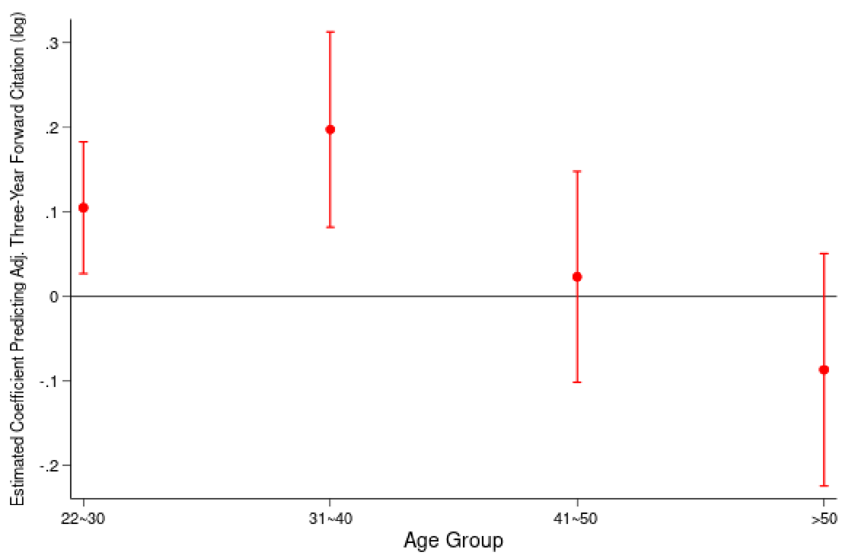


Figure 4: Comparison of Our Measure with Administrative Data (NYC Open Data)

Notes: This graph compares the temporal trends of LinkedIn-based internal hiring rates with those derived from administrative data (NYC Open Data) among employees of the New York City government. The X-axis represents fiscal years, defined as the period from July of the previous calendar year through June of the current year. The Y-axis shows the average share of employees promoted internally in each year.



(a) Inventor-Title FE



(b) Inventor-Title and Employer-Location FE

Figure 5: Breaking Down by Age Cohorts

Notes: These graphs show the association between internal hiring rates and inventors' performance varies by age cohorts. We interacted age cohort with internal hiring rates to predict inventors' performance, and then plot the estimated coefficients for the moderating variable. Model specifications are the same as in Table 1, except that we add age cohort as a moderator. Standard errors are clustered the firm level. The 95 percent confidence intervals are shown in the graphs.

Table 1: Linear Estimation Predicting Innovation using Internal Promotion and External Hiring Rates

	Adjusted Three-Year Forward Citation (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Internally	0.176^{***}	0.110^{***}	0.111^{***}	0.156^{***}	0.100^{***}	0.101^{***}
Promoted Inventors/Num. Inventors	(0.0264)	(0.0271)	(0.0244)	(0.0263)	(0.0270)	(0.0243)
Num. Externally				-0.244^{***}	-0.153^{***}	-0.154^{***}
Hired Inventors/Num. Inventors				(0.0217)	(0.0218)	(0.0195)
Observations	5681821	4852563	4838732	5681821	4852563	4838732
R^2	0.409	0.417	0.420	0.409	0.417	0.420
Fixed Effects:						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title	Yes	Yes		Yes	Yes	
Employer x Location		Yes			Yes	
Inventor x Title x Employer x Location			Yes			Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of analysis is at the individual-year level. Internal promotion and external hiring rates are calculated, respectively, as the number of internally promoted and externally hired inventors divided by the number of inventors, subtracting the focal inventor. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDICES

Appendix Section A. LinkedIn Validation: Comparing LinkedIn Profiles to Administrative Data

In this section, we benchmark LinkedIn-based measures of workforce composition—both demographic and occupational—against three external sources.First, we compare the demographic distributions of LinkedIn users with national statistics from the U.S. Census Bureau (Figure A.1).

[Insert Table A.1 about here]

Second, using American Community Survey (ACS) microdata from IPUMS, we construct NAICS two-digit industry–year measures for 2001–2023 and compare LinkedIn industry–year composition along demographic and occupational dimensions (Figures A.2 and A.3).

[Insert Table A.2 about here]

[Insert Table A.3 about here]

Third, we compare firm-year composition on LinkedIn with the restricted Employer Information Report (EEO-1; Standard Form 100), matching 163,369 LinkedIn firms to EEO-1 records and restricting the sample to firms with at least 30 percent of their workforce represented on LinkedIn. Figures A.4 and A.5 reports the correlations between firms' demographic and occupational compositions measured on LinkedIn and the corresponding Equal Employment Opportunity Commission (EEOC) benchmarks.

[Insert Table A.4 about here]

[Insert Table A.5 about here]

For these validations, we infer each LinkedIn user's gender and race based on their names and profile pictures, and standardize self-reported job titles. Specifically, we use names to estimate the likelihood of a user being a woman, Asian, or Hispanic. To infer the likelihood of being White or Black, we analyze LinkedIn profile photos using two Python packages, DeepFace and OpenCV. Because LinkedIn data does not contain standardized occupational codes, we manually matched self-reported job titles to six-digit Standard Occupational Classification (SOC) codes with the assistance of trained research assistants. Further details on our procedures for inferring race and gender, as well as the occupation-matching process, are documented in Wang, Shin, Zhang (2025).

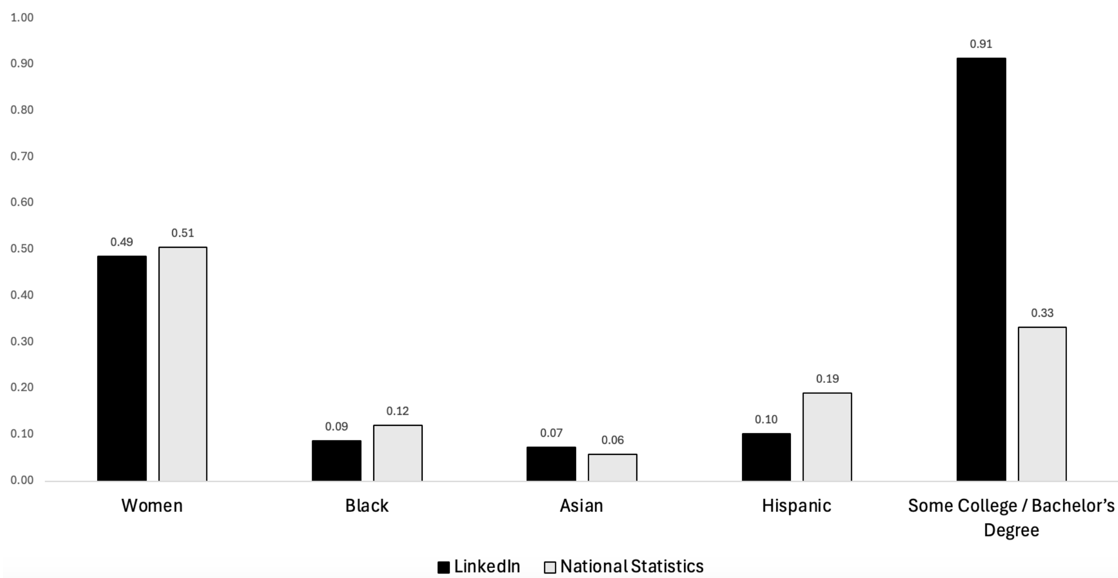
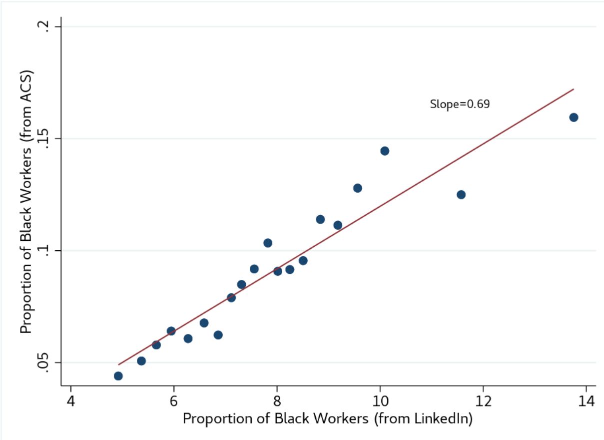
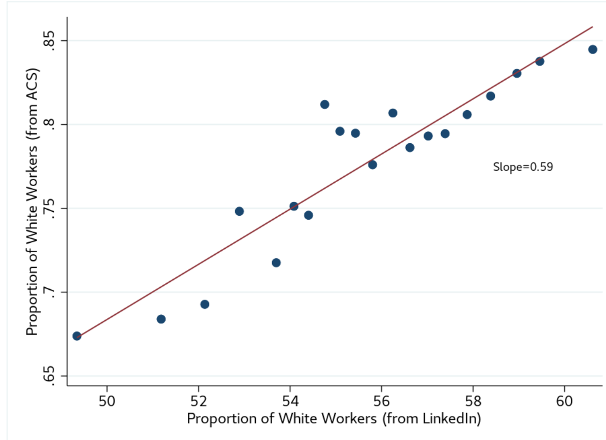


Figure A.1: Comparing LinkedIn to National Statistics

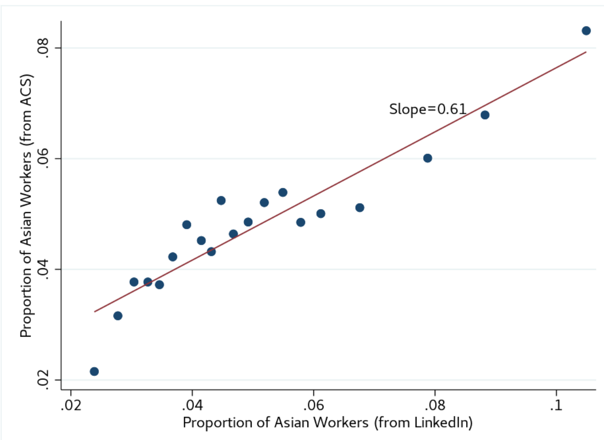
Notes: This graph compares the demographic distribution of LinkedIn users with national statistics from the U.S. Census Bureau's ACS PUMS 5-Year Estimates.



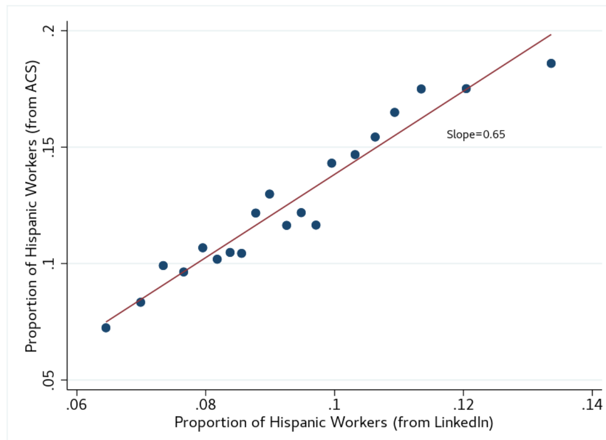
(a) Proportion of Black Workers



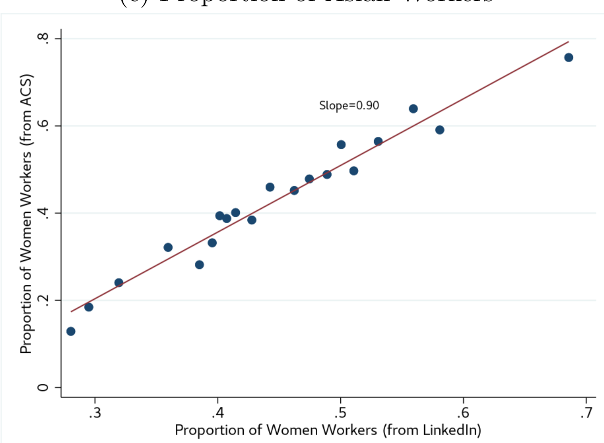
(b) Proportion of White Workers



(c) Proportion of Asian Workers



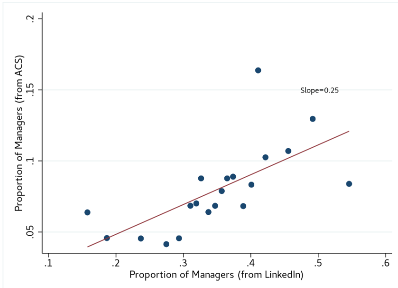
(d) Proportion of Hispanic Workers



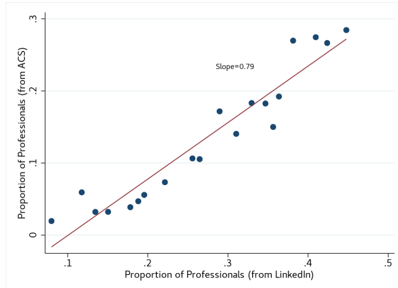
(e) Proportion of Women Workers

Figure A.2: Comparing LinkedIn to ACS Data (Industry-Year): Demographic Composition

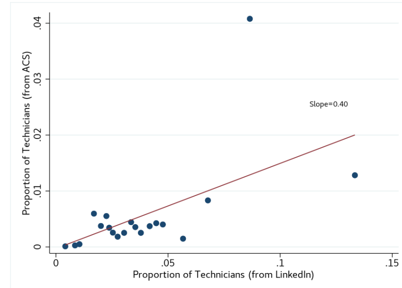
Notes: These graphs descriptively illustrate the association between each NAICS 2-digit industry's workforce composition on LinkedIn and the proportion of workers from different demographic groups in the ACS data. We use the Stata command *binscatter*. All graphs are divided into 20 equal-sized quantile bins of firm-year observations based on the x-axis.



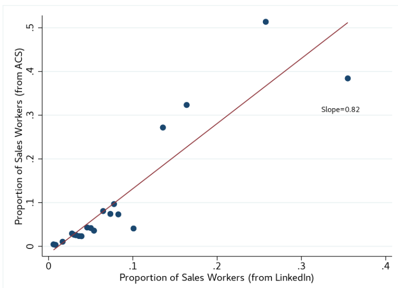
(a) Proportion of Managers



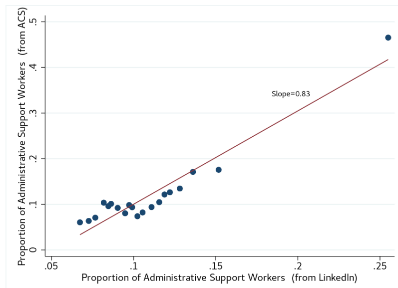
(b) Proportion of Professionals



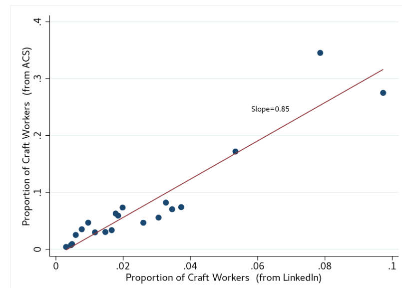
(c) Proportion of Technicians



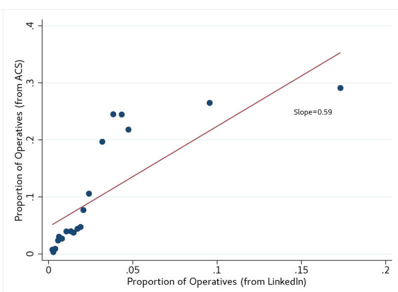
(d) Proportion of Sales Workers



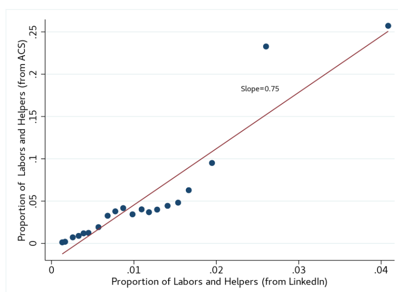
(e) Proportion of Administrative Support Workers



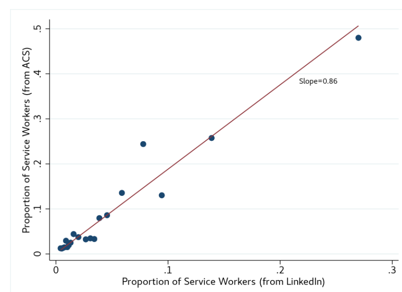
(f) Proportion of Craft Workers



(g) Proportion of Operatives



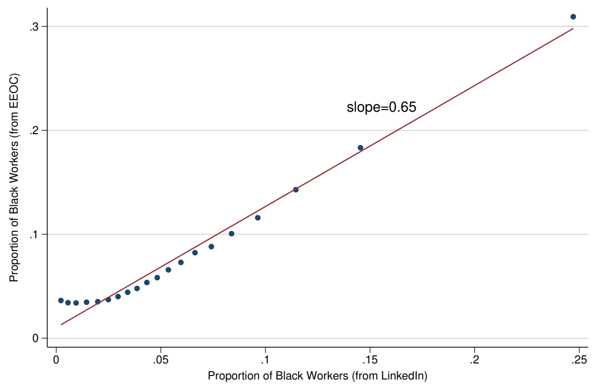
(h) Proportion of Laborers and Helpers



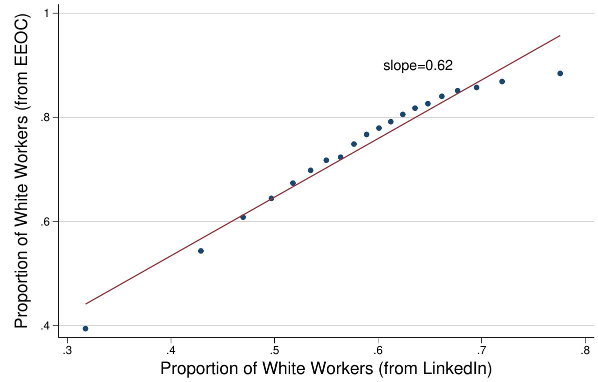
(i) Proportion of Service Workers

Figure A.3: Comparing LinkedIn to ACS Data (Industry-Year): Occupational Composition

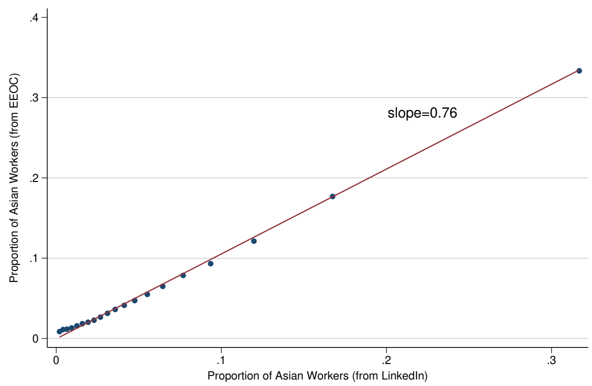
Notes: These graphs descriptively show the association between each NAICS 2-digit industry's occupational composition on LinkedIn and the proportion of workers from different occupational groups in the ACS data. We use the Stata command *binscatter*. All graphs are divided into 20 equal-sized quantile bins of firm-year observations based on the x-axis.



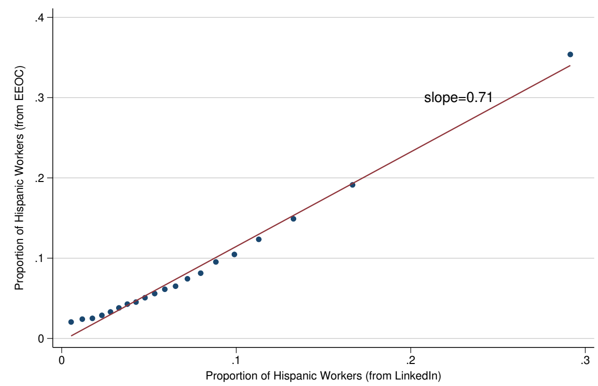
(a) Proportion of Black Workers



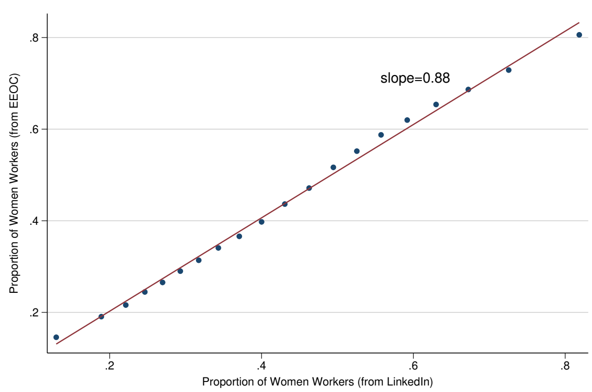
(b) Proportion of White Workers



(c) Proportion of Asian Workers



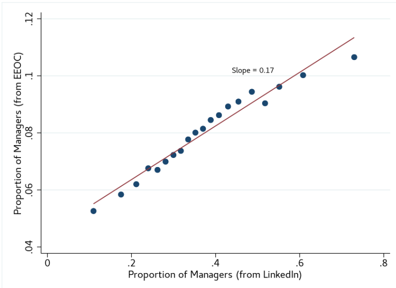
(d) Proportion of Hispanic Workers



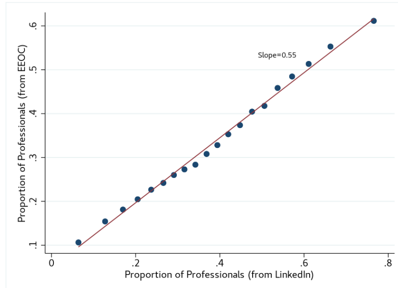
(e) Proportion of Women Workers

Figure A.4: Comparing LinkedIn to EEOC Data (Firm-Year): Demographic Composition

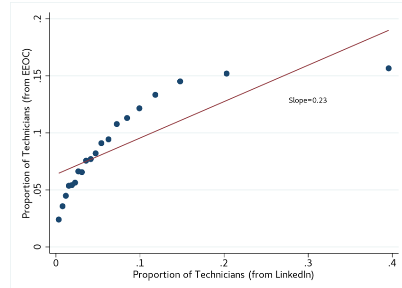
Notes: These graphs descriptively show the association between firms' workforce composition and proportion of workers from different demographic groups in EEOC data. We use the Stata command *binscatter*. Only firms with at least 30 percent of their workforce represented on LinkedIn are included. All graphs are divided into 20 equal-size quantile bins of firm-year observations based on the x-axis.



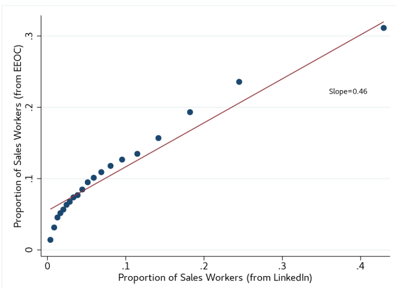
(a) Proportion of Managers



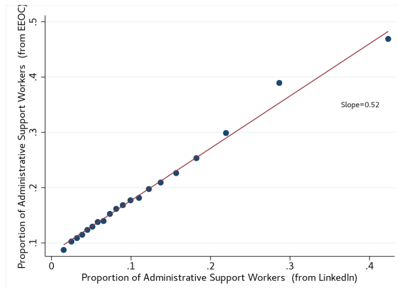
(b) Proportion of Professionals



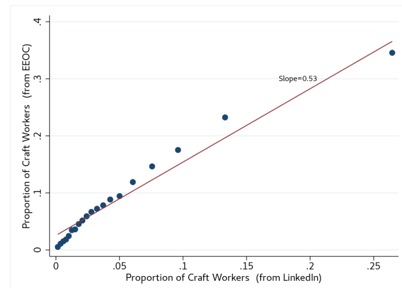
(c) Proportion of Technicians



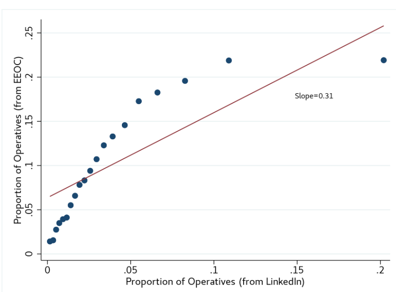
(d) Proportion of Sales Workers



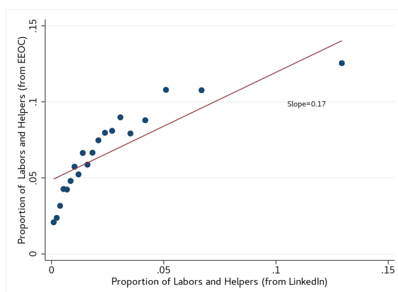
(e) Proportion of Administrative Support Workers



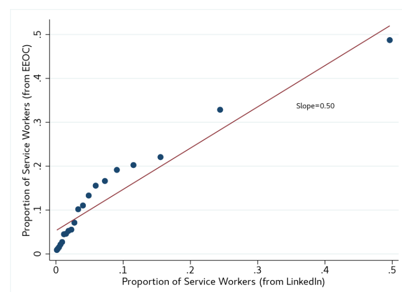
(f) Proportion of Craft Workers



(g) Proportion of Operatives



(h) Proportion of Laborers and Helpers



(i) Proportion of Service Workers

Figure A.5: Comparing LinkedIn to EEOC Data (Firm-Year): Occupational Composition

Notes: These graphs descriptively show the association between firms' occupational composition on LinkedIn and the proportion of workers from different occupational groups in EEO-1 data. We use the Stata command *binscatter*. Only firms with at least 30 percent of their workforce represented on LinkedIn are included. All graphs are divided into 20 equal-sized quantile bins of firm-year observations based on the x-axis.

Appendix Section B. Constructing LinkedIn-USPTO Sample

In this section, we begin by detailing the steps taken to construct our dataset. We then present comparative statistics contrasting inventors successfully matched to LinkedIn profiles and those who were not.

Our patent data is gathered from PatentsView (http://www.patentsview.org), an open data platform collectively built by the United States Patent and Trademark Office (USPTO), the American Institutes for Research (AIR), and the University of California at Berkeley. This platform is a repository for USPTO's administrative data, tracking all files for granted patents and patent applications from 1976 onward. It was updated to March 2025 as of our data download. It includes detailed patent-level measures, ranging from application and grant dates, technology classes, forward and backward citations made to U.S. and foreign patent applications and granted patents by U.S. patents, and citations made to non-patent documents. Specifically, there are three types of technology classes, based on Cooperative Patent Classification (CPC), International Patent Classification (IPC), and USPTO Patent Classification, respectively. In addition, PatentsView includes detailed information on non-inventor applicants, inventors, and assignees, such as their names and disambiguated locations in each patent application. There is also a file about the patent examiners detailing their names, roles, and specialty. Each patent has a unique ID that can be used to link all information mentioned above.

A patent assignee refers to the individual or entity that has been legally granted the ownership rights to a patent. At the time of patent application, the original assignee is typically the inventor or the inventor's employer (the employer assignee). The assignee data in PatentsView report the first assignee for each patent, which is usually either the inventor or the employer assignee. Before September 16, 2012, patents were required to be issued initially to a human inventor, and ownership could be transferred to an employer only through assignment by the inventor. After the enactment of the America Invents Act (AIA), this requirement was removed, allowing both human inventors and their employers to be listed directly as patent owners. For patents filed after 2012, the employer assignee can therefore be identified as the assignee in PatentsView records.

To identify the employer assignee in pre-2012 cases, we used the non-inventor applicants file from PatentsView and the Patent Assignment Dataset. The Patent Assignment Dataset includes the exact date of each assignment transfer, and we can identify the first and the second assignees based on the date. If a patent has a non-inventor organization listed on the non-inventor applicants file, it is regarded as the employer assignee; otherwise, we identify the employer assignee through the Assignment Dataset. It is worth mentioning that the assignment dataset does not include the complete assignment history, as reporting assignment changes is not required. However, it is in the interest of assignors and assignees to report it. For patents that could not be tracked to a unique employer assignee, we used LinkedIn data to identify the inventors' employers.

We track inventors' employment history using LinkedIn profiles data, which contains around 500 million users' profiles spanning more than 140 industries. There are six files in the LinkedIn data, including users' work experiences, education, certification, language skills, emails, basic information (e.g. name, imputed gender and birth year, and current location). Each user is assigned a unique identifier, used to link these files. Using work experiences file, we can track users' previous and recent employers, and the start and end year of each employment, as well as their workplace location and employers headquarter location.

Inventor-LinkedIn User Match

We proceeded to match U.S. inventors with LinkedIn profiles following the steps below. Numbers in parentheses are matched unique inventors after each step.

Step 1 (2,717,320): Match on last name, first name, middle name, and gender. We begin with exact matching on first and last names. For unmatched cases, we apply fuzzy matching using an embedding model by computing the cosine similarity between all possible first–last name pairs. Pairs with similarity scores of 0.95 or higher are further evaluated using the GPT API to identify the most likely matches. We then incorporate middle name and gender in the matching process. Since middle names are often missing from LinkedIn profiles, we treat a pair as matched if the middle name is missing in LinkedIn but present in the inventor data.

Step 2 (1,863,927): We clean and standardize employer assignees and LinkedIn companies' names. We conduct both exact and fuzzy matching on firm names between two datasets. We drop those inventors who have no employer assignees matched to any of companies in the LinkedIn data.

Step 3 (488,036): Match on employment history. Specifically, we require there is at least one overlapping employer between the inventor and the LinkedIn user, and drop those pairs in which the inventor has no employer assignee matched to any of the employers on the matched LinkedIn user's profile.

Step 4 (488,036): Match on employment history. This step resolves some of the ambiguous matches by only keeping those pairs that share the largest number of overlapping employers.

Step 5 (486,809): Match on employment history. This step resolves ambiguous matchers by only keeping those pairs in which the matched LinkedIn user has at least one employment started before or in the year when the inventor filed the first patent application at that firm.

Step 6 (486,431): Match on employment history. This step resolves multiple matchers by only keeping those pairs in which the matched LinkedIn user has at least one employment ended after or in the year that the inventor filed the last patent application at that firm. We do not require an exact match on employment history as it is very common that inventors do not have any patent applications at some firms, and we can only observe the employer assignees at which they have patents. So normally, we would expect that the number of employments exceeds the number of employer assignees for each inventor-LinkedIn pair.

Step 7 (485,717): Match on employment history. This step further disambiguates ambiguous matchers by only keeping those pairs that have the largest number of employments that meet the requirement in step5. For those one-to-one matches, we require they meet either the requirement in step 5 or in step 6.

Step 8 (446,058): Match on employment history. After previous steps, there are still some LinkedIn profiles that are matched to multiple inventors, and we resolve those many-to-one matches by only keeping those pairs that share the largest number of employers, and manually go through remaining multiple matchers to identify the best match.

Step 9: Remove employer assignees where inventors were not employed.

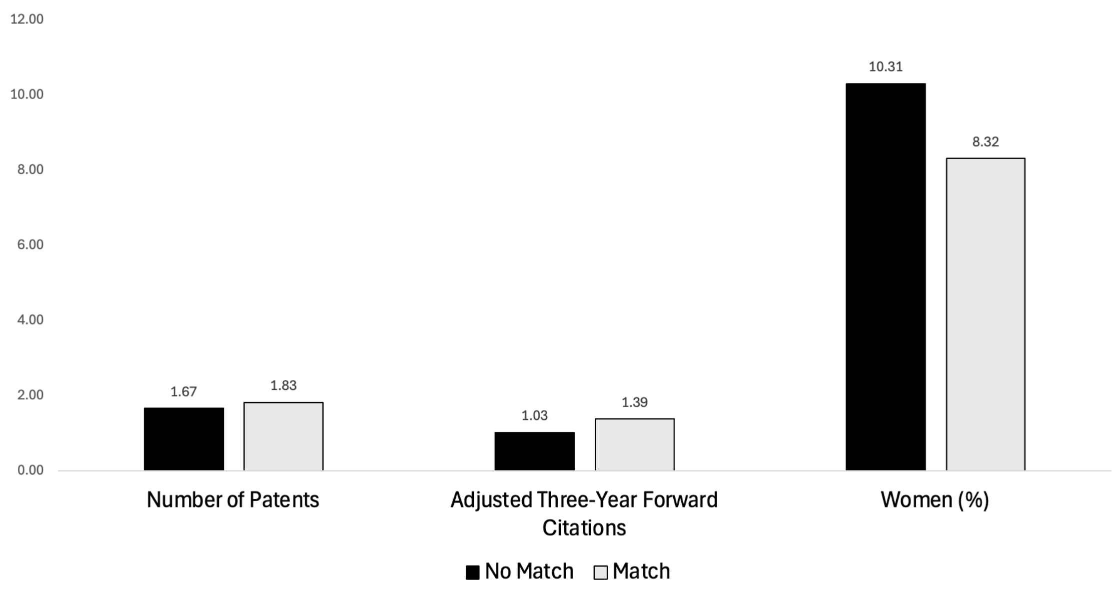


Figure B.1: Match vs. No Match

Appendix Section C. Sample Distribution

This section provides descriptive statistics and pairwise correlations for the key variables in our LinkedIn-USPTO matched sample. Observations are measured at the inventor-year level.

[Insert Table C.1 about here]
[Insert Table C.2 about here]
[Insert Table C.3 about here]

Table C.1: Summary Table

	Mean	Min	Max	SD
Key Measures				
Num. Internally Promoted Inventors/Num. Inventors	0.1	0.0	1.0	0.1
Num. Externally Hired Inventors/Num. Inventors	0.1	0.0	1.0	0.1
Innovation Measures				
Adjusted Three-Year Forward Citation (Counts)	0.3	0.0	4206.1	4.5
Num. Patent Applications (Counts)	0.7	0.0	1759.0	2.9
Num. Patents (Counts)	0.3	0.0	383.0	1.4
Patent Values ($)	2.7	0.0	15313.0	32.6
Co-authored Adjusted Three-Year Forward Citation (Counts)	0.1	0.0	1283.5	1.3
Control Variables				
Num. Employees (Hundreds)	154.8	1.0	7295.4	443.3
Firm Innovation Capacity (Hundreds)	282.2	0.0	1640.0	320.2
Prop. of R&D Employees	0.1	0.0	1.0	0.1
Prop. of Managers	0.3	0.0	1.0	0.1
Employee Average Tenure (Years)	5.0	0.0	35.0	2.5
Observations	5681821			

Table C.2: Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Num. Internally Promoted Inventors/Num. Inventors	1.000							
(2) Num. Externally Hired Inventors/Num. Inventors	0.045	1.000						
(3) Adjusted Three-Year Forward Citation	0.013	0.011	1.000					
(4) Num. Employees	0.020	0.059	-0.003	1.000				
(5) Firm Innovation Capacity	-0.057	0.171	-0.040	0.133	1.000			
(6) Prop. of R&D Employees	0.097	0.132	0.011	0.035	0.014	1.000		
(7) Prop. of Managers	0.135	0.046	0.012	-0.113	-0.100	0.066	1.000	
(8) Employee Average Tenure	-0.003	-0.338	-0.018	0.143	-0.044	-0.198	0.009	1.000
Observations	5681821							

Table C.3: Correlation Matrix Among Different Innovation Measures

	(1)	(2)	(3)	(4)	(5)
(1) Adjusted Three-Year Forward Citation	1				
(2) Num. Patent Applications	0.148	1			
(3) Num. Patents	0.353	0.513	1		
(4) Patent Values	0.190	0.281	0.373	1	
(5) Co-authored Adjusted Three-Year Forward Citation	0.903	0.144	0.325	0.163	1
Observations	5681821				

Appendix Section D. Alternative Measures of Internal Hiring Rate

In our primary tables, we define the internal hiring rate as the ratio of internally promoted inventors to the total number of inventors within each firm annually. In this section, we replicate our main results in Table 1 using four alternative measures of internal hiring rate.

First, we reconstruct our main measure by adjusting how we identify promotions. In our sample, approximately 60 percent of internal occupational changes involve moving from a lower-seniority position to a higher-seniority one. For our primary analysis, we do not differentiate between those occupational changes that result in lower or the same subsequent levels of seniority and those that lead to higher seniority positions. To assess the robustness of our findings, we recalculate the internal hiring rate, considering only those internal occupational changes that result in higher-seniority positions as promotions. The results presented below align with our main analyses.

[Insert Table D.1 about here]

Finally, in Table D.2, we establish a three-year window and recompute the internal hiring rate each year, using the count of both internally promoted and externally hired inventors within this window. For example, the internal hiring rate of Apple Inc. in 2009 is calculated as the total number of internally promoted inventors divided by the sum of internally promoted and externally hired inventors from 2007 to 2009. Our results continue to remain valid even when considering this alternative measure, further affirming the robustness of our findings. This three-year internal hiring rate consistently exerts a significantly positive influence on inventors' innovation outputs across all models. It is worth noting that we have excluded firm fixed effects from this analysis. This decision stems from the fact that our three-year measure is nearly specific to the employer, and incorporating firm fixed effects would absorb a significant amount of variation.

[Insert Table D.2 about here]

Table D.1: Linear Estimation Predicting Innovation Using Alternative Internal Promotion Criteria

	Adjusted Three-Year Forward Citation (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Internally Promoted Inventors/Num. Inventors	0.255***	0.171***	0.170***	0.236***	0.162***	0.162***
	(0.0284)	(0.0291)	(0.0261)	(0.0283)	(0.0290)	(0.0261)
Num. Externally Hired Inventors/Num. Inventors				-0.234***	-0.140***	-0.142***
				(0.0228)	(0.0229)	(0.0204)
Observations	5681821	4852563	4838732	5681821	4852563	4838732
R^2	0.409	0.417	0.420	0.409	0.417	0.420
Fixed Effects:						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title	Yes	Yes		Yes	Yes	
Employer x Location		Yes			Yes	
Inventor x Title x Employer x Location			Yes			Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table uses a stricter seniority rule. Internal promotions are within-firm moves to higher-seniority roles. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.2: Linear Estimation Predicting Innovation using Three-Year Rolling Internal Promotion and External Hiring Rate

	(1)	(2)	(3)	(4)	(5)	(6)
Three-Year Rolling Num. Internally	0.453***	0.179***	0.179***	0.441***	0.186***	0.186***
Promoted Inventors/Num. Inventors	(0.0530)	(0.0524)	(0.0524)	(0.0529)	(0.0526)	(0.0526)
Three-Year Rolling Num. Externally				-0.0820*	0.0650	0.0650
Hired Inventors/Num. Inventors				(0.0351)	(0.0381)	(0.0381)
Observations	6609380	5663146	5663146	6609380	5663146	5663146
R^2	0.400	0.410	0.410	0.400	0.410	0.410
Fixed Effects:						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title		Yes			Yes	
Employer x Location		Yes			Yes	
Inventor x Title x Employer x Location			Yes			Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table computes internal and external promotion rates using a three-year rolling window (data from previous three years). The unit of analysis is at the individual-year level. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Section E. Alternative Measures of Employee Innovation

We construct six different metrics measuring inventors' innovative activity. In this Appendix Section, we first discuss our steps of constructing each of these metrics and the difference among them. Then, at the end of this section, we present the results predicting the five metrics that are not included in the main analyses, *Number of Patent Applications, Number of Patents, Patent Values, Unadjusted Three-Year Forward Citation,* and *Coauthor Adjusted Three-Year Forward Citation*, respectively using Table 1 model specifications.

Number of Patent Applications: our first metric measures an inventor's total number of patents produced at each firm in each year of employment, regardless of whether they were granted or not. While this metric captures an inventor's productivity, it does not account for the quality of their innovations. Patent application process is time-consuming and costly as it typically takes two years and costs around $8,000, which deters some people from applying, but anyone who creates or uncovers something that meets the requirements for a patent is technically eligible to apply for one. A highly productive inventors from a large corporation may afford to file numerous patent applications, but only a few of those may be approved. Additionally, it's worth noting that only published patent applications are accessible to the public. If an inventor can certify that she has no intention of filing a patent application in a foreign country, she can request nonpublication of her application. As a result, the number of applications attributed to an inventor may not include all the applications they have filed. In addition, it is more common for applications to omit assignee information, as confirmed by PatentsView. Therefore, we measure application counts at the inventor-year level.

Number of Patents: to address the limitations of our first metric and better capture an inventor's innovative ability, our second metric measures the total number of granted patents for each inventor. This measure reflects inventors' capability of producing successful patents, which considers the quality of patents to some degrees. Besides, unlike patent applications, all granted patents — including those that were withdrawn after being granted — are available to the general public. Therefore, this approach can effectively capture all of an inventor's successful patents. However, this measure still cannot distinguish between patents in terms of their novelty or importance since some patents are filed solely for defensive purposes.

Unadjusted Three-Year Forward Citation: to differentiate breakthrough innovations from less novel ones, we follow a common approach used in innovation literature and calculate our third metric as the total number of three-year forward citations received by each inventor's patents. This metric reflects the number of times a patent has been cited within three years since its grant year and is aggregated at the inventor-employer-year level. In addition to measuring novelty, this metric can also indicate the economic significance of an innovation, as it has been shown to be highly correlated with the market value of associated firms.

Adjusted Number of Three-Year Forward Citation: this is our main measure. Citation rates exhibit significant variations across time and technological classes. For instance, on average, patents granted in 1963 received 2.9 citations, but this figure increased to 7.17 for patents granted in 1986, and dropped to 0.04 in 1999. Moreover, patents related to computers and communication typically receive 6.44 citations, while mechanical patents receive only 4 citations on average. One limitation of the raw citation rates is that it does not account for these patterns. To address this, we first calculate the average number of citations received by patents granted in the same year and primary technology class. We then construct our fourth metric by dividing the citation count of each patent by the corresponding average number.

Coauthor Adjusted Three-Year Forward Citation: we divide each patent and its subsequent citations by the number of co-inventors. For instance, a median patent in the full sample has two inventors. In the case of two inventors, we assign each inventor one-half of the subsequent citations that the patent receives within the first three years.

Patent Values: first proposed by Kogan et al. (2017), patent value captures the economic importance of innovation outputs. Specifically, they measure the economic value of each innovation by examining the stock market's reaction to news about individual patents. Following each patent's grant, they compute the firm's abnormal stock return over a three-day window surrounding the grant date. This abnormal return is then converted into a dollar value by multiplying it by the firm's market capitalization just prior to the grant. To adjust for inflation over time, we use their patent values deflated to 1982 dollars using the Consumer Price Index (CPI). We measure each inventor's annual patent value at an assignee by summing the values of their patents granted that year.

To assess the robustness of our findings to different functional forms, we re-estimate our main model using inverse hyperbolic sine and modified log transformation suggested by Chen and Roth (2024). All results remain robust.

Table E.1: Linear Estimation Predicting Alternative Innovation Measures using Internal Promotion and External Hiring Rates

	Num. Applications (log)		Num. Patents (log)		Patent Values (log)		Unadjusted Citations		Co-authored Adjusted Citations	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Num. Internally	0.0564***	0.0367***	0.0558***	0.0243**	0.0713***	0.0343	0.0596***	0.0372***	0.122***	0.0772***
Promoted Inventors/Num. Inventors	(0.00863)	(0.00813)	(0.00842)	(0.00768)	(0.0177)	(0.0176)	(0.0102)	(0.00946)	(0.0190)	(0.0176)
Observations	5681821	4838732	5681821	4838732	5681821	4838732	5681821	4838732	5681821	4838732
R^2	0.591	0.596	0.511	0.525	0.476	0.485	0.443	0.455	0.415	0.425
Fixed Effects:										
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title x Employer x Location		Yes		Yes		Yes		Yes		Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table uses five alternative measures of innovation performance as outcomes. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Section F. Using Different Sample Thresholds

In Table 1, we exclude firm-year cells that have fewer than five inventors. In this section, we examine our results using different thresholds. Table F.1 presents the results at four different thresholds for the number of vacancies, employing the same model specifications as in Table 1. The internal hiring rate consistently demonstrates a positive association with both the number of patents and citations for inventors across all thresholds. As we move from lower to higher vacancy thresholds, the impact of the internal hiring rate becomes increasingly pronounced.

Table F.1: Linear Estimates Predicting Adjusted Three-Year Forward Citations: Using Different Sample Thresholds

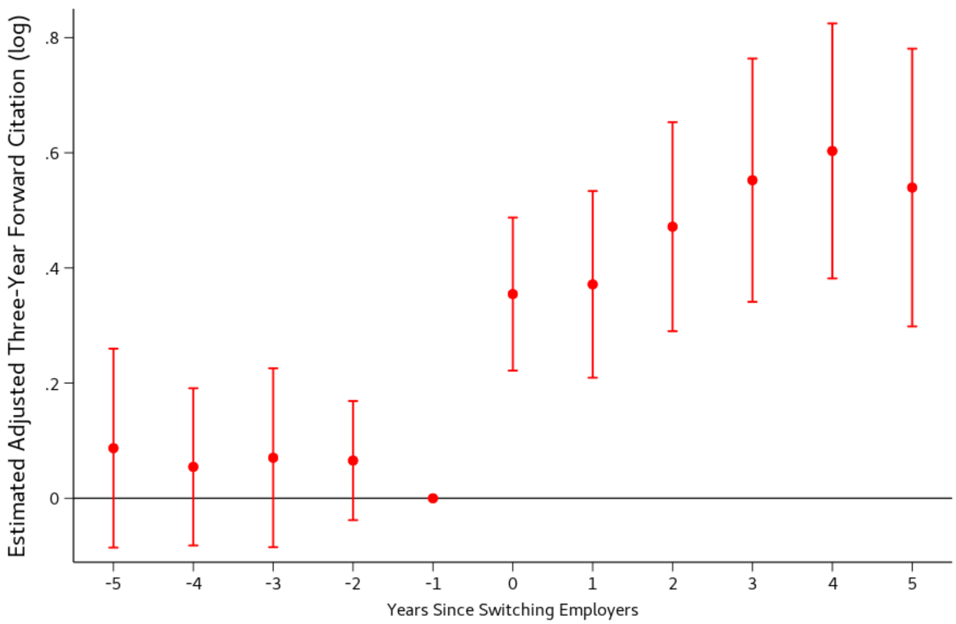
	# of Inventors	(1)	(2)	(3)
Num. Internally	>= 0	0.0613***	0.0348***	0.0355***
Promoted Inventors/Num. Inventors		(0.0162)	(0.0167)	(0.0151)
	>= 3	0.0988***	0.0556***	0.0568***
		(0.0264)	(0.0271)	(0.0244)
	>= 10	0.262***	0.155***	0.156***
		(0.0448)	(0.0455)	(0.0409)
	>= 20	0.350***	0.204**	0.205**
		(0.0695)	(0.0693)	(0.0624)
Fixed Effects:				
Calendar Year		Yes	Yes	Yes
Years in the Workforce		Yes	Yes	Yes
Years on the Job		Yes	Yes	Yes
Inventor x Title		Yes	Yes	
Employer x Location			Yes	
Inventor x Title x Employer x Location				Yes
Control Variables		Yes	Yes	Yes

Notes: This table tests alternative sample thresholds: the minimum number of inventors required for a firm to be included. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

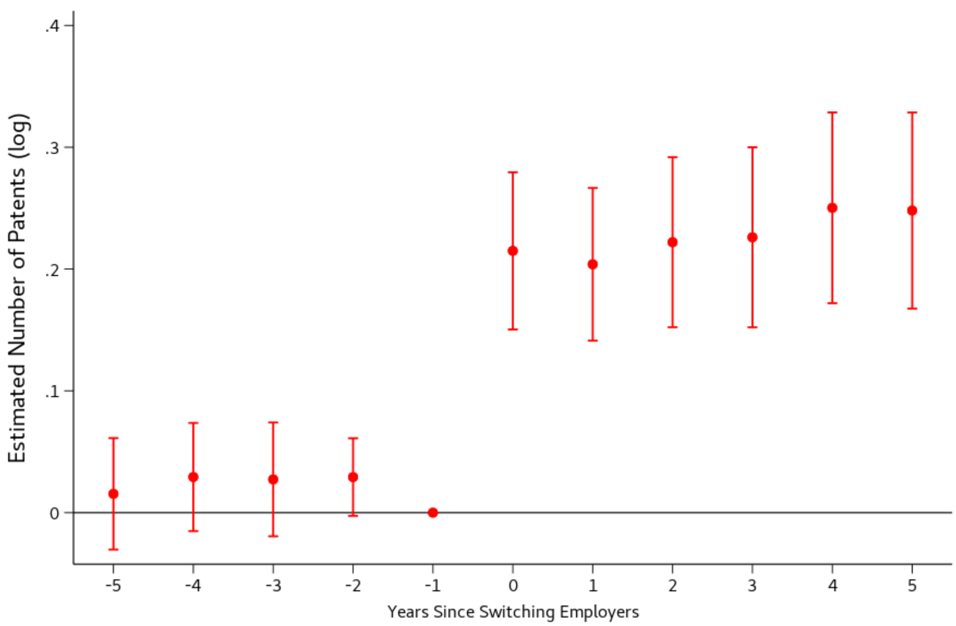
Appendix Section G. Event Study: Comparing Moves to Firms with Higher vs. Lower Promotion Rates

In this section, we examine how inventors' innovation performance varies depending on the internal promotion rate of the firms they join. We focus on inventors who began their careers at the same firm but later moved to firms with different internal promotion rates. Specifically, we compare those who moved to firms where the internal promotion rate was at least ten percentage points higher with those who moved to firms where the rate was at least ten percentage points lower.

To reduce complications from multiple job transitions, we restrict the analysis to each inventor's first observed move—from their initial employer to their second. We also exclude movers for whom no counterpart could be identified who started at the same firm and moved in the opposite direction in terms of internal promotion rates. All control variables from Table 1 are included, along with inventor–title dyadic fixed effects and location controls.



(a) Adjusted Three-Year Forward Citation



(b) Number of Patents

Figure G.1: Performance Gap Between Inventors Moving to Firms with Higher vs. Lower Internal Promotion Rates

Appendix Section H. Heterogeneity by Productivity and Gender

In this section, we replicate our main results across different sub-samples. First, we divide the sample and conduct separate analyses for "star" inventors—those in the top 10% by patent count—and "non-star" inventors. Non-star inventors in our sample hold an average of 4.03 patents and 1.35 weighted citations, which is comparable to the unmatched inventors' averages of 5.7 patents and 1.23 weighted citations.

[Insert Table H.1 about here]

Second, we split the sample by inventor gender in Table H.2. Inventors' gender is estimated based on first names.

[Insert Table H.2 about here]

Table H.1: Linear Estimation Predicting Innovation using Internal Promotion and External Hiring Rates

	Top Inventor			Non-Top Inventor		
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Internally	0.341***	0.201**	0.200***	0.118***	0.0747***	0.0752***
Promoted Inventors/Num. Inventors	(0.0642)	(0.0642)	(0.0583)	(0.0212)	(0.0224)	(0.0201)
Observations	1519533	1287948	1285481	4162280	3563982	3553244
R^2	0.458	0.468	0.470	0.275	0.284	0.286
Fixed Effects:						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title	Yes	Yes		Yes	Yes	
Employer x Location		Yes		Yes		
Inventor x Title x Employer x Location			Yes			Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table stratifies the sample by performance. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table H.2: Linear Estimation Predicting Innovation using Internal Promotion and External Hiring Rates

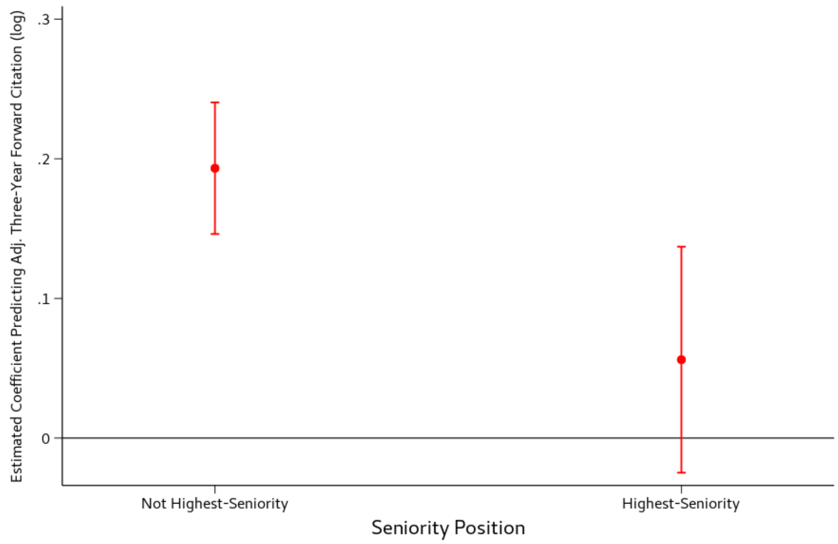
	Woman			Man		
	(1)	(2)	(3)	(4)	(5)	(6)
Num. Internally	0.194***	0.131**	0.134**	0.182***	0.113***	0.114***
Promoted Inventors/Num. Inventors	(0.0452)	(0.0483)	(0.0429)	(0.0267)	(0.0277)	(0.0249)
Observations	680785	585078	583506	4624911	3970696	3960146
R^2	0.394	0.405	0.406	0.411	0.419	0.421
Fixed Effects:						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes
Inventor x Title	Yes	Yes		Yes	Yes	
Employer x Location		Yes		Yes		
Inventor x Title x Employer x Location			Yes			Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table stratifies the sample by gender. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

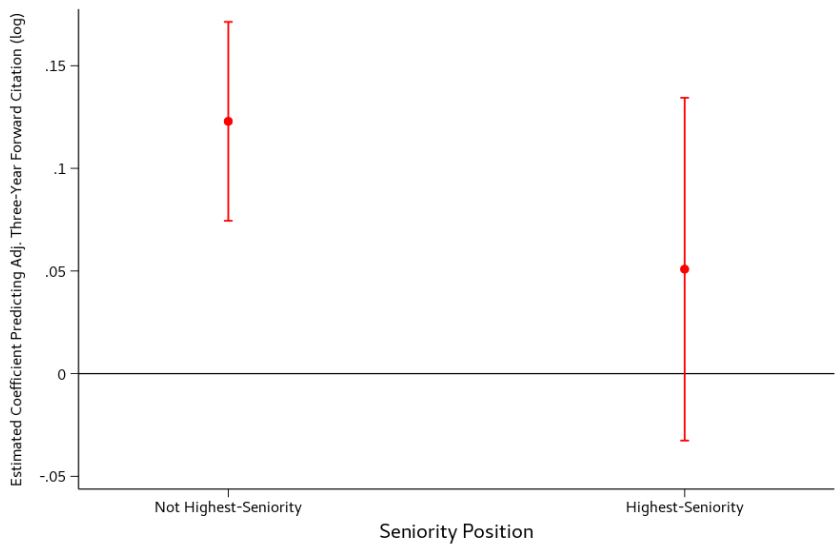
Appendix Section I. Comparison to Inventors in the Most Senior Position

These graphs compare how the relationship between internal hiring rates and inventors' performance differs between those occupying the most senior position in a firm and those who do not. If an inventor already holds the top role within the organization, she is presumably less influenced by promotion incentives. For each firm-year, we identified the most senior role held by each inventor and created a dummy variable indicating whether the inventor occupied the top position within the firm in that year. We then interacted this indicator with internal hiring rates to predict inventors' performance. The graphs display the estimated coefficients for this moderating variable. Model specifications follow those in Table 1, with the top-position indicator included as a moderator. Standard errors are clustered at the firm level, and the figures display ninety-five percent confidence intervals.

[Insert Table I.1 about here]



(a) Inventor-Title FE



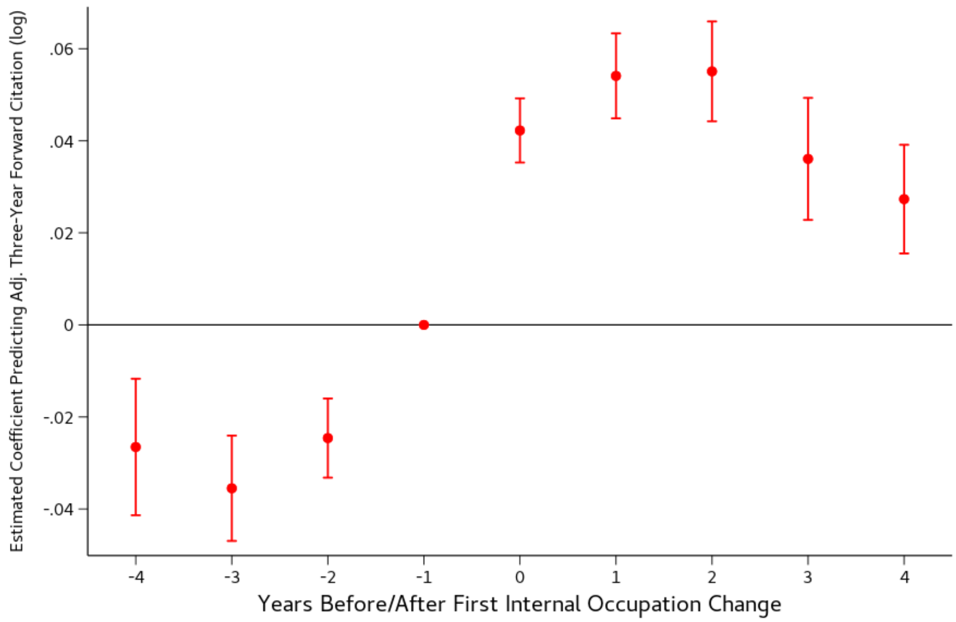
(b) Inventor-Title and Employer-Location FE

Figure I.1: Breaking down by The-Most-Senior-Position

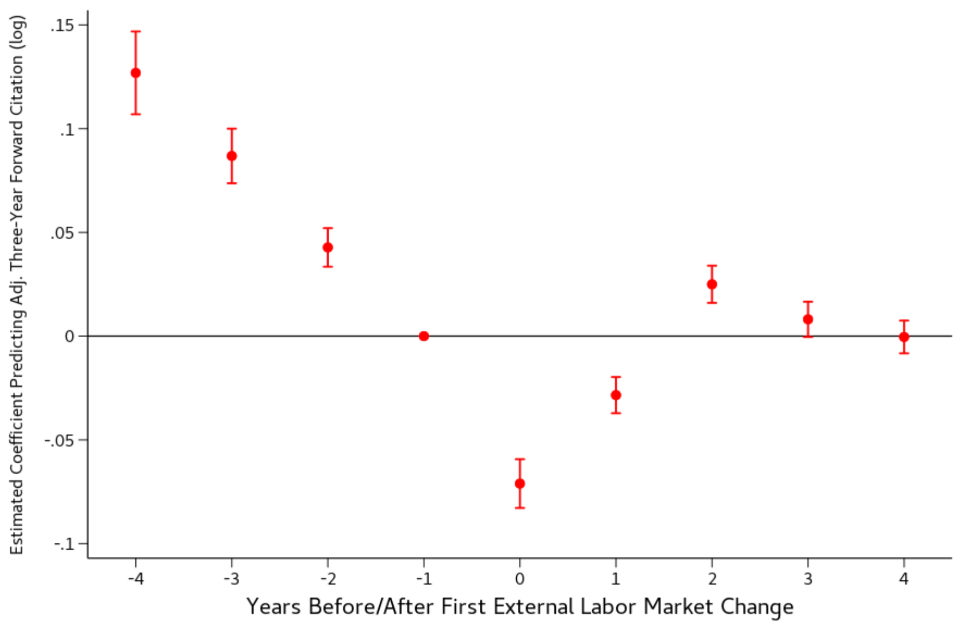
Appendix Section J. Performance of Internally Promoted versus Externally Hired Inventors

This section compares the performance of internally promoted versus externally hired inventors over time, as measured by adjusted three-year forward citation counts. We analyze only an inventor's first promotion or external move. Figure J.1 plots the performance trajectory for each group relative to one year before the event, while Figure J.2 isolates the performance gap between them. Table J.1 presents the linear regression results, which include employer-occupation fixed effects, the controls from Table 1, and the moderating effect of job tenure.

[Insert Figure J.1 about here]
[Insert Figure J.2 about here]
[Insert Table J.1 about here]

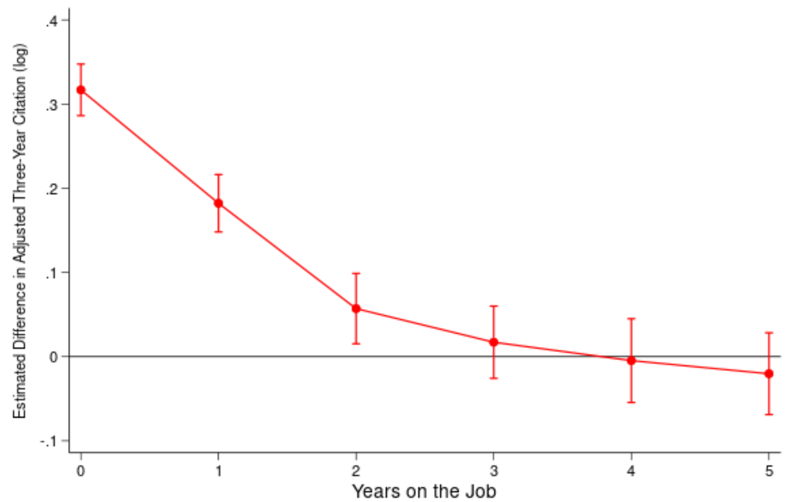


(a) Internal Promotions

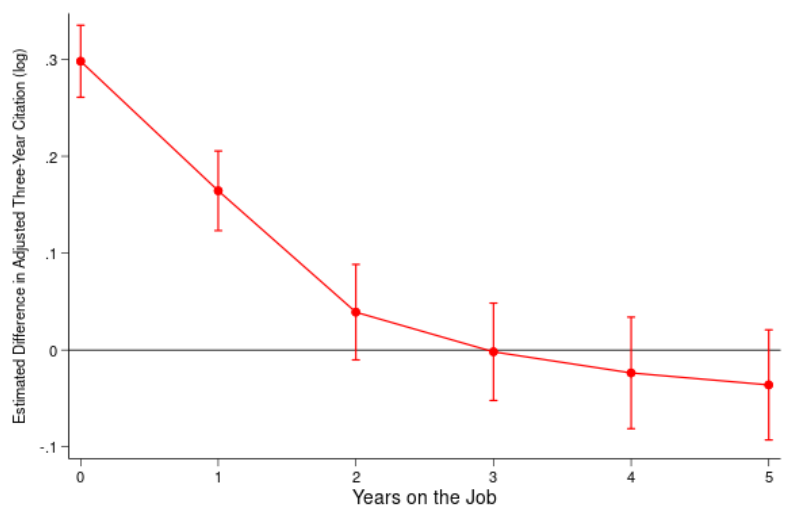


(b) External Hirings

Figure J.1: Changes in Inventor Performance after Promotion/Hiring



(a) Title FE



(b) Employer-Title FE

Figure J.2: Performance Gap Between Internally Promoted and Externally Hired Inventors

Table J.1: Linear Estimation Predicting Innovation: Performance Difference Between Internally Promoted and Externally Hired Inventors

	Adjusted Three-Year Forward Citation (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Internally Promoted Inventor	0.152***	0.148***	0.123***	0.274***	0.279***	0.259***
	(0.0124)	(0.0108)	(0.0111)	(0.0182)	(0.0169)	(0.0202)
Internally Promoted Inventor x Years on the Job				-0.0747***	-0.0790***	-0.0785***
				(0.00484)	(0.00517)	(0.00586)
Observations	2274815	2225117	2152388	2274815	2225117	2152388
R^2	0.049	0.231	0.365	0.050	0.233	0.367
Fixed Effects:						
Calendar Year	Yes	Yes	Yes	Yes	Yes	Yes
Years in the Workforce	Yes	Yes	Yes	Yes	Yes	Yes
Years on the Job	Yes	Yes	Yes	Yes	Yes	Yes
Occupation		Yes			Yes	
Employer x Title			Yes			Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table compares performance between internally promoted and externally hired inventors. The unit of analysis is at the individual-year level. Control variables include the logged number of professional employees, the proportion of R&D employees, the logged average employee tenure, the proportion of managers, and the logged cumulative number of patents. Standard errors clustered at the firm level are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$