Coveting your neighbor's worker: IPOs, talent reallocation, and innovation

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February 1, 2026

Abstract

We examine talent reallocation following a private firm's transition to public equity markets. We explore this question using detailed employment and project-level data in the biopharmaceutical industry. We define a firm's peers at a precise level using overlap in project development portfolios based on therapeutic disease categories. Our results show that firms that go public significantly ramp up poaching of skilled labor from their still-private peers. Recruitment efforts are centered on scientists and high-experience workers, indicating that going public helps firms to attract talented workers directly from their competitors. At the same time, recently public firms exhibit an out-migration of less talented labor to their still-private peers. This reallocation of talented agents to recently-public firms and away from competitors is reflected in project outcomes—firms that are successful in attracting talented agents exhibit stronger outcomes in terms of progress in project development phases, project initiations, and eventual project approvals. Our results illustrate the nature of labor reallocation following the transition to public equity markets at a granular level as well as provide a mechanism for the competitive advantages afforded to going-public firms.

Keywords: Initial public offerings, labor mobility, labor reallocation, innovation, investment, drug development, public equity markets, healthcare finance.
JEL classification: G21, G31, G32, I11, I15

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1 Introduction

How do recently public firms shape the allocation of talent and skilled labor within an industry? An initial public offering (IPO) can confer significant competitive advantages for the going-public firm, where the influx of capital, increased public visibility, and enhanced value/liquidity of stock and options used as compensation can be used to attract talented workers. Understanding possible labor flows when a firm goes public within an industry can help elucidate the precise mechanisms by which firms benefit from the public listing. At the same time, reshaping the labor market may put still-private peer firms at a competitive disadvantage against the public firms that can better attract labor, pointing to potential significant negative spillover effects for firms that remain private.

We explore the above question in the context of the biopharmeutical industry. In particular, we examine the possible migration of labor for firms that are competitive *peers* to the going-public firm. We define a firm's peers based on overlap of project development portfolios, with two firms being classified as peers if both are actively developing drugs that target the same detailed therapeutic indication category (measured via ICD-10 categories). The advantage of this approach is that our granular project-level data on biopharmeutical firms permits us to observe project progress within firms—for both ones that go public and those that remain private—before and after the IPO decision, as well as to identify competitive peers of each firm. We combine this project-level data with detailed worker-level data from Revelio Labs, which allows us to track labor movement between firms and also other details of a worker's employment history, such as education and job titles. In our analysis we consider only high-skilled labor, such as scientists, clinical research associates, and project managers, among others.

Our empirical design employs a stacked difference-in-differences (DID) specification with a window of six years before and after the IPO event. We find that a recently-public firm is 19.1 percentage points more likely to poach a skilled worker directly from one of its competitor firms, an economically sizable increase of 258% relative to the sample mean

poaching likelihood. In terms of poaching from peers that are still private, we document an increase of 8.2% percentage points in poaching propensity, representing an even greater increase of 290% relative to the sample mean. These findings establish that recently-public firms significantly ramp up their poaching of workers directly from their competitor firms, and that poaching is more intense from still-private peer firms.

We further examine the nature of the labor reallocation noted above based on specific worker types. We find that poaching from still-private peers by the recently-public firm is centered on scientists, workers with specialized human capital who are arguably the most critical for the drug development process. Private firms in this industry have three scientists on average, so the loss of one can be devastating for a private firm. Moreover, recently-public target workers with greater experience and more often poach from smaller firms.

We additionally show that the labor migration following IPOs is not a one-way street, but rather that the talent reallocation following IPOs also includes out-migration or departures from the going-public firm to peer firms after the IPO event. We conduct this analysis at the worker level and find that the propensity of workers to depart to peer firms also increases significantly following the transition to public equity markets, with a 50% increase in departure propensity. We also find that less-experienced workers are relatively more likely to move from IPO firms to their private peers. Collectively, the results suggest that an IPO results in a labor reallocation that places the newly-public firm at a competitive advantage—its private peers lose more-experienced workers to the IPO firm and replaces those lost workers with less-experienced workers gained from the IPO firm.

Given the worker movement we document following IPOs, an important open question is: how does this labor reallocation affect the innovation process? To answer this question, we leverage our detailed project-level data to examine the link between the documented labor reallocation and innovation outcomes. We find that recently-public firms that have poached more workers from their still-private peers exhibit disproportionately *greater* innovation outcomes, while departures do not appear to negatively impact these same outcomes.

In particular, the number of clinical projects which advance to the next phase in project development nearly doubles for firms with the greatest number of poaches. When we consider the net change in workers (defined as poached workers minus departures), we again observe significant improvement in innovation efficiency and project development among firms with greater net inflows of skilled labor. Importantly, when distinguishing between high- and low-experience workers, we find that the effect is concentrated among high-experience workers. This provides evidence that it is specifically the ability of IPO firms to poach more-skilled workers that leads to the improvement in project outcomes.

We analogously investigate the impact of the talent reallocation on still-private peer firms following the IPO in order to fully explore equilibrium effects. The results show that still-private firms exhibit significant declines in clinical project progress if a competitor firm undertook an IPO in the previous three years. We further find that this effect is driven by the peer firm having their workers poached by the recently-public competitor firm, particularly of the high-experienced labor (workers with at least three years of experience). These results suggest that the out-migration of skilled labor from still-private peers negatively impacts these firms while benefiting the recently-public firms that hire these workers. Stated differently, the labor reallocation that occurs following a firm's transition to public equity markets is accompanied with a "redistribution" of innovation efficiency from still-private firms to recently public ones.

Our study is related to several literatures. A recent stream of literature considers the labor market effects of IPOs. Babina et al. (2020) study the employment size and earnings of workers following IPOs and document that IPO firms generally increase in size, but wages of current employees do not exhibit significant increases. Aghamolla et al. (2025) explores employment and other outcomes in the hospital industry following IPOs, and show evidence of operational expansions and spillover effects for healthcare prices. We contribute to this literature by examining employment and labor allocation decisions at a more granular level and connecting hires and departures with an IPO firm's still-private competitor firms. As

such, we document novel findings that IPO firms increase poaching significantly from their still-private peer firms. Furthermore, our ability to track individual projects within a firm permits us to provide evidence that these poaches are primarily aimed at highly-skilled labor critical for project development, and how labor reallocation influences project outcomes and innovation at both the going-public firm and the firm's still-private competitors.

Relatedly, a number of studies consider the capital market effects of IPOs on other firms within an industry, such as Hsu et al. (2010), Chemmanur and He (2011), Chod and Lyandres (2011), and Aghamolla and Thakor (2022b). We contribute to this literature by documenting the labor market effects of IPOs on competitor firms, particularly those that remain private. Likewise our study contributes to the literature examining the innovation outcomes of going public, such as Bernstein (2015), Acharya and Xu (2017), and Aghamolla and Thakor (2022a). We complement this literature by documenting an important mechanism through which recently-public firms bolster innovation—by poaching talented workers from their competitors. As such, our study also relates to the literature examining the determinants of IPO propensity, such as Lerner (1994), Pagano and Röell (1998), Brau et al. (2003), Lowry (2003), Kim and Weisbach (2008), Chemmanur et al. (2010), Gao et al. (2013), Ewens and Farre-Mensa (2020), and Larrain et al. (2025). We build on this literature by showing the labor market advantages of going public over still-private peer firms.

A small but growing literature at the intersection of finance and labor investigates examines employment outcomes and earnings in the context of firm privatization (Olsson and Tåg (2025)), corporate diversification (Beaumont et al. (2025)), access to credit (Bai et al. (2018)), mergers and acquisitions (Lagaras (2025), Herkenhoff et al. (2025)), and executive relative performance evaluation (Bloomfield et al. (2025)). We contribute to this literature by documenting how the transition to public equity markets can reshape the allocation of talent within an industry. Finally, our paper is related to the recent literature on peer effects in capital markets, such as Tse and Tucker (2010), Leary and Roberts (2014), Kaustia and Rantala (2015), Grennan (2019), Foroughi et al. (2021), and Seo (2021). Our analysis exam-

ines the outcomes of project-level peers following a competitor's IPO and shows that firms that remain private exhibit negative spillover effects in terms of hiring and worker retention.

2 Data and Empirical Methodology

2.1 Data Description

We construct a dataset of project outcomes, labor flows, and IPO decisions for private and public firms operating in the U.S. biopharma industry.

We obtain detailed data on drug development projects from the Cortellis Life Sciences Healthcare Database. The Cortellis Database sources information on drugs in development and approved drugs from clinical trial registries, FDA submissions, patent filings, company press releases, and regulatory filings. For each drug candidate, Cortellis provides information about the disease it targets (e.g., pancreatic cancer, hematology, etc.) as well as its development history—trial initiations/suspensions, the start/end date of each phase of the clinical trial process, developmental milestones, FDA regulatory actions, and other information. This allows us to track the progress of each project in a firm's development portfolio, and also identify the therapeutic area that a firm operates in, a key aspect of our identification strategy which we describe in more detail in the next section. Importantly, Cortellis includes drug development information for both private as well as public firms, enabling us to track firm outcomes both before and after a firm does an IPO.

We obtain detailed employee history data from Revelio Labs, a comprehensive workforce intelligence database that standardizes publicly available professional profiles (e.g., from LinkedIn and other sources). The data include information on employees' job titles, skills, education, and employment history across firms and over time, which allows us to track employee movement between firms. We match firms from Cortellis to the Revelio Labs data by name and industry. More details about the matching procedure are provided in Appendix B.

With this combined sample of drug development projects and employee profiles within firms, then we manually match firms with Compustat to identify publicly-traded firms and obtain information on IPO dates. For our main specifications, we drop any firm in our sample that had gone public prior to 2000, the beginning of our sample period.

Our final sample consists of 16,740 firm-year observations for 3,076 unique firms from 2000 to 2024. We observe a total of 475 IPOs during our sample period; Figure 1 shows the number of IPOs by biopharma firms in our sample over time. We also run regressions at the worker level, for which our sample consists of 1,890,299 worker-year observations for 249,191 unique employees.

2.2 Empirical Methodology

Our primary empirical specification explores outcomes for firms before and after they undertake an IPO, compared with firms that stay private. More specifically, we run the following stacked difference-in-differences (DID) regression at the firm-year level:

$$Y_{i,c,t} = \beta PostIPO_{i,c,t} + \gamma_{i,c} + \delta_{c,t} + \epsilon_{i,c,t}, \tag{1}$$

In regression (1), $PostIPO_{i,c,t}$ is an indicator variable that takes a value of one if firm i has undertaken an IPO as of year t, and zero otherwise, in cohort c. Since firms go public at different times over our sample, we estimate equation (1) using a "stacked" DID specification (i.e., Gormley and Matsa (2011), Cengiz et al. (2019)) in which we form a stacked sample consisting of cohorts of treated and control firms for each year, including cohort-year and cohort-firm fixed effects. Specifically, for each IPO year, we construct a cohort spanning twelve years around the IPO, from six years prior to the IPO to six years after. Within each cohort, firms that go public that year constitute the treatment group, while firms that remain private throughout the twelve-year window serve as the control group.[1] With the inclusion

[1]Our stacked sample consists of 133,080 firm-year observations. Firms may appear in multiple cohorts for two reasons. First, firms that never go public during the sample period (i.e., never-treated firms) can

of cohort-firm and cohort-year fixed effects, $\gamma_{i,c}$ and $\delta_{c,t}$, the coefficient β thus estimates the within-cohort marginal impact of a firm going public on the outcome variable compared to a firm that has remained private.

A key aspect of our analysis is tracking labor flows between firms following IPOs. As a result, for our main outcome variables $Y_{i,t}$ in regression (1), we exploit the granularity of our data to construct firm-level measures of employee "poaching" from peer firms at both the intensive and extensive margins. Following Aghamolla and Thakor (2022b), we identify peers as firms that operate in the same therapeutic area. In particular, two firms are classified as peers if they have projects in their development portfolios that are in the same ICD-10 area. We then construct variables that track whether a firm has hired (i.e. "poached") an employee away from a peer firm in a given year, as well as what type of employee was hired (i.e., a scientist, lab technician, etc.). We also construct variables that distinguish whether the poaching was from any peer firm or from private peer firms.

In additional analyses, we explore the consequences of such poaching on innovation efficiency, proxied by whether a drug project progresses to the next phase. We also consider broader innovation outcomes, such as whether a firm has started new development projects, new drugs, or new therapeutic areas.

Panel A of Table 1 provides summary statistics for the variables in our analysis; detailed data definitions are included in Appendix A. Panel B provides the median number of worker, separated by worker type, for firms that remained private over the sample as well as firms that eventually do an IPO. Prior to doing an IPO, treated firms have a similar number of employees to non-treated firms. Post-IPO, the number of employees in total and across all categories increases significantly. Panel C summarizes the mean new flow of employees over our sample for IPO firms (focal firms) and for their private peers. On average, IPO firms experience a new inflow of workers while their private peers experience a net outflow of workers, consistent with an IPO providing firms with a competitive advantage by allowing

serve as controls in all cohorts. Second, firms that go public at least six years after the focal IPO year (i.e., not-yet-treated firms) may serve as controls in earlier cohorts prior to their own IPOs.

them to poach workers from private peers. Our empirical tests explore this mechanism.

3 Results: Labor Reallocation following IPOs

3.1 Talent Poaching Following IPOs

Panel A of Table 2 provides estimation results for regression (1) at the firm-year level, examining poaching of workers from peer firms as the outcome variable. In column (1), the dependent variable is an indicator variable that takes a value of one if the focal firm poached at least one worker from a peer firm, and zero otherwise. The coefficient is positive and significant, indicating that an IPO results in the focal firm being roughly 19 percentage points more likely to poach employees from its peers, a 2.5-fold increase over the sample unconditional mean of 5.3%. In Column (2), we define the dependent variable to take a value of one if the focal firm poached at least one worker from a *private* peer firm, and zero otherwise. We again find a positive and significant coefficient, which provides evidence that an IPO puts a firm in a position to raid talent from its peers that remain private. Columns (3) and (4) run similar regressions, but define the dependent variable as the number of workers poached instead of an indicator variable; we obtain equivalent results. The magnitudes suggest that, on average in a given year, recently-public firms poach roughly 18 additional workers from peer firms and roughly 4 additional employees specifically from private peer firms.[2]

In Panel B of Table 2, we run a similar specification to Panel A, but structure our test at the *pair*-year level. We form pairwise combinations of each set of peers in our dataset, with each pair being a unit of observation. We then define poaching within a pair as a movement of workers from the non-IPO firm to the IPO firm. We obtain similar results to our firm-level specifications.

[2]Given 475 IPOs over our sample period of 23 years, this translates to roughly 20 IPOs per year, which gives the yearly total number of poaches when multiplied by the coefficient estimates in columns (3) and (4). The larger magnitudes for all peer firms relative to private peer firms reflect the fact that private firms are, on average, significantly smaller than IPO firms, as shown in Table 1.

Inference via our DID regressions rests upon the parallel trends assumption, whereby IPO firms and non-IPO firms exhibit parallel trends prior to the IPO. To test this, we estimate dynamic treatment effects in Figure 2. Given the issues documented in the econometrics literature about interpreting treatment effects in staggered DID designs with two-way fixed effects, we include parallel trends for our stacked specification and also using the methodology of Callaway and Sant'Anna (2021) for robustness. As shown in the figure, both the treated and control firms do not exhibit differential trends in terms of poaching prior to an IPO, but afterwards the IPO firms significantly increase their poaching of workers relative to the non-IPO firms.

In Table 3, we focus on the types of workers that recently-public firms hire by separating our poaching outcome variable by job title. Panel A examines the propensity of IPO firms to poach workers of different types of jobs. We find that IPO firms primarily poach workers that have technical or scientific expertise from peer firms—scientists, clinical research associates, and lab technicians—as opposed to roles not requiring such expertise, such as sales representatives and project managers. Panel B runs the same specification but examines the number of each type of employee poached; the magnitudes imply that the average IPO firm poaches 0.32 (6×0.054) additional scientists over the six years post-IPO, or roughly 11% of its pre-IPO scientific workforce (based on a median of three scientists).

Table 4 explores other characteristics of workers that are poached by IPO firms. We find that recently-public firms poach more-experienced workers, and furthermore poach more workers from smaller private peers. The Chi-square differences indicate that the differences in magnitudes are statistically significant.[3]

3.2 Heterogeneity in Talent Poaching

A key aspect of going public is gaining capital via equity markets, thus bestowing a competitive advantage for IPO firms against their rivals (e.g., Aghamolla and Thakor (2022b)).

[3]We present differences across other worker characteristics in Appendix Table A.1.

Our previous results suggest that one channel through which firms are able to do so is by acquiring talent from competitors. If these channels are indeed at play, we would expect a stronger poaching effect attached to "larger" IPOs, i.e., ones where firms gain a greater competitive advantage.

To explore this mechanism, we split our $PostIPO$ treatment variable at the median across different measures of IPO size. More specifically, we define $PostIPO^{Large}$ to take a value of one if the IPO firm is above-median size versus all biopharma IPO firms in that given year (and zero otherwise), and $PostIPO^{Small}$ to take a value of one if the IPO firm is below-median size versus all biopharma IPO firms in that given year (and zero otherwise). We examine total assets, number of employees, and number of development portfolio projects in the IPO year as measures of size.

Table 5 provides the results. Across the measures, we find larger effects attached to larger IPOs. This is consistent with the notion that the IPO confers a competitive advantage for firms which enables them to acquire talent from their competitors.

3.3 Employee Movement Decisions

Our previous results at the firm-level provide evidence of focal IPO firms acquiring talent from their competitors, suggesting a reallocation of talent in the industry following an IPO. In this section, we leverage our microdata to shed additional light on this reallocation by tracking individual employee movement between biopharma firms around IPOs.

To do so, we run an equivalent specification to regression (1) at the worker-year level:

$$Leave_{w,i,c,t} = \beta PostIPO_{i,c,t} + \gamma_{i,c} + \delta_{c,t} + \epsilon_{w,i,c,t}, \tag{2}$$

In regression (2), $Leave_{w,i,c,t}$ is an indicator variable that equals one if worker w departs firm i and secures a new job within one year of t, and zero otherwise.[4] We define this outcome

[4]In Table A.3 of the Appendix, we show that our results are robust to defining the departure window alternatively as 6 months, 2 years, or 3 years.

variable separately based on the destination of the worker—whether the employee is leaving to join a peer firm, a public or private peer firm, or a startup. In line with regression (1), $PostIPO_{i,c,t}$ is an indicator variable that takes a value of one if firm i in cohort c has undertaken an IPO as of year t, and zero otherwise. Regression (2) is thus a linear probability model that estimates the propensity of an worker to leave a focal firm following an IPO.

Table 6 provides the results. Interestingly, once a focal firm goes public, we also see a significantly increased propensity for its workers to leave the firm and join its competitors. Thus, in additional to an IPO firm gaining workers from its competitors, some of the IPO firm's existing workers choose to move to its competitors, both private and public. We do not find evidence that these workers leave to start new firms.[5] These results suggest that IPOs result in bilateral worker movement between IPO firms and competitors, resulting in a true reallocation of labor in the industry rather than simply the focal IPO firm gaining labor.[6]

Figure 3 provides the dynamic treatment effects corresponding to the results in Table 6. The figure suggests that the parallel trends assumption holds in this setting as well—there are no differential trends for employee departures at treated firms compared to control firms prior to the IPO, but following the IPO there is a significant departure of employees from the focal firm.

Table 7 sheds more light on which type of employees leave (focusing on movement to private peers). We find that employees with relatively less experience are more likely to leave IPO firms to join private firms. We also find that employees with PhDs and scientists—high-skilled employees with technical expertise—are more likely to leave for competing firms following IPOs. Combined with the previous results, this suggests a reallocation of labor that places IPO firms at a competitive advantage—IPO firms poach more-experienced labor from private firms, while less-experienced labor moves away from IPO firms and joins private

[5] A worker is considered to have moved to a startup if the worker's new job title includes "chief", "founder", "ceo", "cfo", "coo", or "entrepreneur".

[6] In general, there is no difference in the propensity of workers to exit across IPO firm size; this is shown in Appendix Table A.2.

firms.

4 Results: IPOs and Innovation Outcomes

In this section, we examine the real consequences of talent reallocation following IPOs by examining innovation outcomes for IPO firms as well as peers.

4.1 Innovation Efficiency following IPOs

We first leverage our project-level data to establish a baseline result for the effect of the IPO on the focal firm's innovation. To do so, we re-run regression 1 with an outcome variable that proxies for the innovation efficiency of the firm. Specifically, we construct an indicator variable—$Progress$—which takes a value of one if a project in firm i's development portfolio progresses to the next phase of the FDA clinical trial process in year t, and zero otherwise. We estimate regression 1 at both the firm-level, which tracks the likelihood of any project in the firm's development portfolio proceeding to the next phase, as well as at the project-level, which tracks the likelihood of a given project in the firm's portfolio to progress to the next phase.[7]

Following Cunningham et al. (2021) and Li et al. (2023), the idea is that an improvement in the firm's innovation ability (induced, for example, by having better researchers) will lead to a higher likelihood of proceeding to the next phase of the FDA clinical trial process. For robustness, we also construct a firm-level version of $Progress$ that tracks the number of projects in a firm's development portfolio that proceed to the next phase in a given year, which we call $NumProgress$.

Table 8 provides the estimation results. We find strong evidence that drug projects at IPO firms are significantly more likely to progress in the development process, which is evidence in support of the IPO improving the efficiency of the focal firm's innovation

[7]When estimating at the firm level, we control for the size of the firm by including the number of drug projects in the firm's pipeline.

process. In Table A.4 of the Appendix, we also examine other innovation outcomes, such as the likelihood of initiating a new project, a new project in a different therapeutic area, and the likelihood of a new drug getting FDA approval. We find positive and significant effects for these outcomes, indicating that the level of innovation increases in addition to the progress of existing projects.[8] Figure 4 provides the dynamic treatment effects—as before, there are parallel trends between treated and control firms with respect to innovation efficiency prior to the IPO, but after the IPO there is a significant increase for the IPO firms relative to the still-private firms.

4.2 Talent Poaching and Innovation Efficiency

The results in the previous section point to a significant increase in innovation efficiency following IPOs. A channel this may operate through is via labor—the previously-documented poaching of additional talent after an IPO may lead to an improvement in innovation outcomes.

In order to provide evidence of this channel linking poaching and innovation outcomes, we run the following regression at the firm-year level:

$$Progress_{i,c,t} = \beta Net\,Poach\,IPO_{i,c,t} + \gamma_{i,c} + \delta_{c,t} + \epsilon_{i,c,t}, \tag{3}$$

In regression (3), $Net\,Poach\,IPO$ is the cumulative net number of employees that firm i has poached from its private peers as of year t, defined as the number of workers packed from private peers minus the number of workers that left the IPO firm to go to private peers. $Net\,Poach\,IPO$ thus measures net poaching of talent from private peers following IPOs.

In Table 9, the estimation results are provided. The coefficient for $Net\,Poach\,IPO$ is positive and significant, indicating that innovation efficiency is greater when an IPO firm has poached more employees from private peers. This provides evidence that the improvement

[8] This is also consistent with evidence in Gupta and Kao (2024).

in innovation efficiency is linked to the ability of IPO firms to poach talent from still-private competitors.[9]

In columns (2) and (4), we also explore heterogeneity to further illuminate this channel. In particular, an improvement in the innovation process due to labor reallocation should be linked to hiring more skilled employees. We proxy for this by examining net poaching of experienced employees. More specifically, we split $Net\ Poach\ IPO$ into $Net\ Poach\ IPO^{High\ Exp}$ and $Net\ Poach\ IPO^{Low\ Exp}$, depending on the experience level of the employees (with high experience defined as employees with more than three years of experience). Consistent with the labor reallocation channel, we find that a greater net poaching of high-experience employees is positively associated with improved innovation efficiency, while this is not the case for low-experience employees.

4.3 Poaching and Private Peer Innovation

Our results thus far point to IPOs enabling firms to poach experienced employees from private peers, which results in an improvement in project outcomes at the firm undertaking the IPO. In order to better understand the equilibrium consequences of this labor reallocation, in this section we explore how this affects innovation outcomes at these peers that remain private.

In order to do so, we follow the methodology of Aghamolla and Thakor (2022b) and define a $Peer\ IPO_{t-1,t-3}$ variable that takes a value of one if a private firm had at least one peer firm undertake an IPO over the past three years, and zero otherwise.[10] We then run the following regression for the sample of private firms:

$$Progress_{i,t} = \beta Peer\ IPO_{i,[t-1,t-3]} + \gamma_i + \delta_t + \epsilon_{i,t}, \tag{4}$$

[9] In Appendix Table A.5, we show that the effects are driven by positive effects from poaching, while the effects of workers exiting are primarily insignificant.

[10] Given the long gestation periods inherent in drug development, with the average project taking 8 years to complete from start to finish (i.e., Lo and Thakor (2022)), we define this variable over a window to account for the fact that the effect on innovation likely takes time to manifest. Consistent with this, we find insignificant effects with a shorter window.

We also run regression (4) at the project level, including ICD-10 fixed effects.

Panel A of Table 10 provides the results. We find that private firms whose peers do an IPO experience a *reduction* in project progression (innovation efficiency). This is consistent with these private firms being at a competitive disadvantage when their peers go public. To example whether this effect is driven by the labor channel—poaching of experienced employees by IPO firms—in Panel B we interact $Peer\,IPO_{[t-1,t-3]}$ with variables that track the number of high/low-experience employees entering or leaving the firm from $t-1$ to $t-3$. We find that the negative effect on project progress is amplified when high-experience employees leave the private firm, but there is a counterveiling effect when low-experience workers leave. When combined with our previous results, this suggests that the deleterious effects on project progress stem from public firms poaching high-experience employees following IPOs.

Private biotechnology firms are small, with a median of 3 scientists (Table 1). As a result, one would expect that the negative effects of poaching will be concentrated amongst these firms if labor is a significant driver of the results. In Table 11 we show that this is the case—the negative effects are focused on smaller firms with fewer scientists after their peers undertake an IPO.

5 Conclusion

This study examines how initial public offerings (IPOs) reshape the allocation of human capital and innovation outcomes. Leveraging rich, project-level and worker-level data from the drug development industry, we find that IPOs are associated with simultaneous talent poaching from private peer firms—after going public, firms become significantly more likely to attract employees from private peers. We further show that IPOs are linked to improved innovation outcomes, and these gains are closely tied to talent flows: cumulative net inflows of workers from private peers are positively associated with project progress and approvals. Finally, we show that private firms exposed to peers' IPOs experience declines in project

progress, especially when they suffer net talent outflows. Overall, the findings highlight IPOs as pivotal events that reallocate skilled labor, enhance innovation at newly public firms, and impose competitive externalities on private peers.

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Figure 1: Time Trend of IPOs

This figure plots the number of biopharma IPOs in each year from 2001 to 2023.

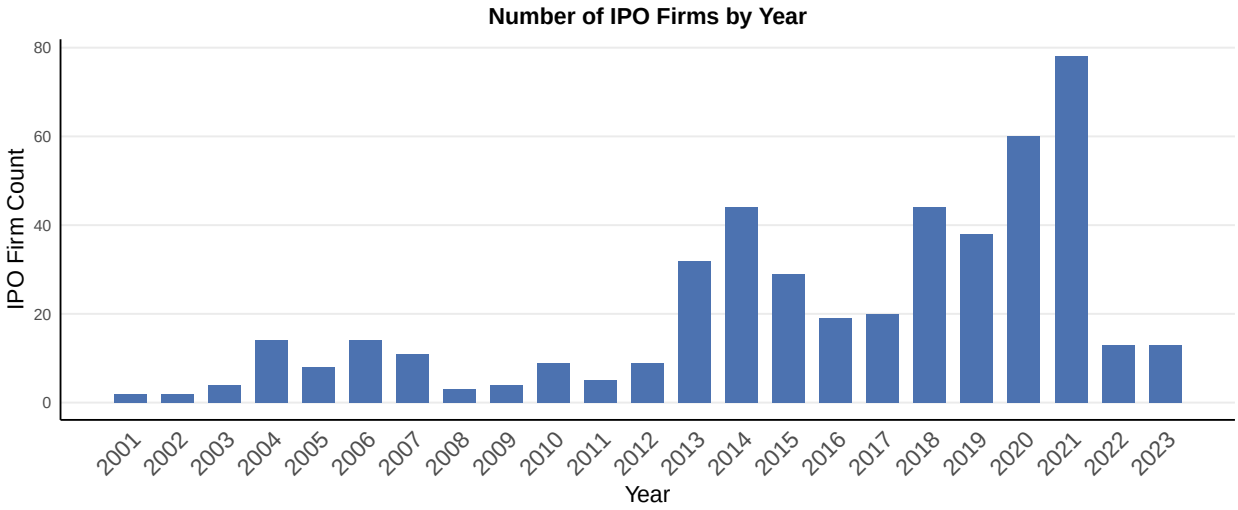

Figure 2: Dynamic Treatment Effects for Talent Poaching

This figure plots the dynamic coefficient estimates of $PostIPO$ from regression (1), estimated at the firm-year level, for each year surrounding the IPO year (year 0). The outcome variables are $Poach$, an indicator variable that equals one if a firm poaches at least one employee from its peers (top graph) or private peers (bottom graph), and zero otherwise. $NumPoach$ is the number of employees poached from its peers (top graph) or private peers (bottom graph). Error bars represent 95% confidence intervals. Dynamic effects are estimated via a stacked DID methodology (orange plots) or using the methodology of Callaway and Sant'Anna (2021) (green plots).

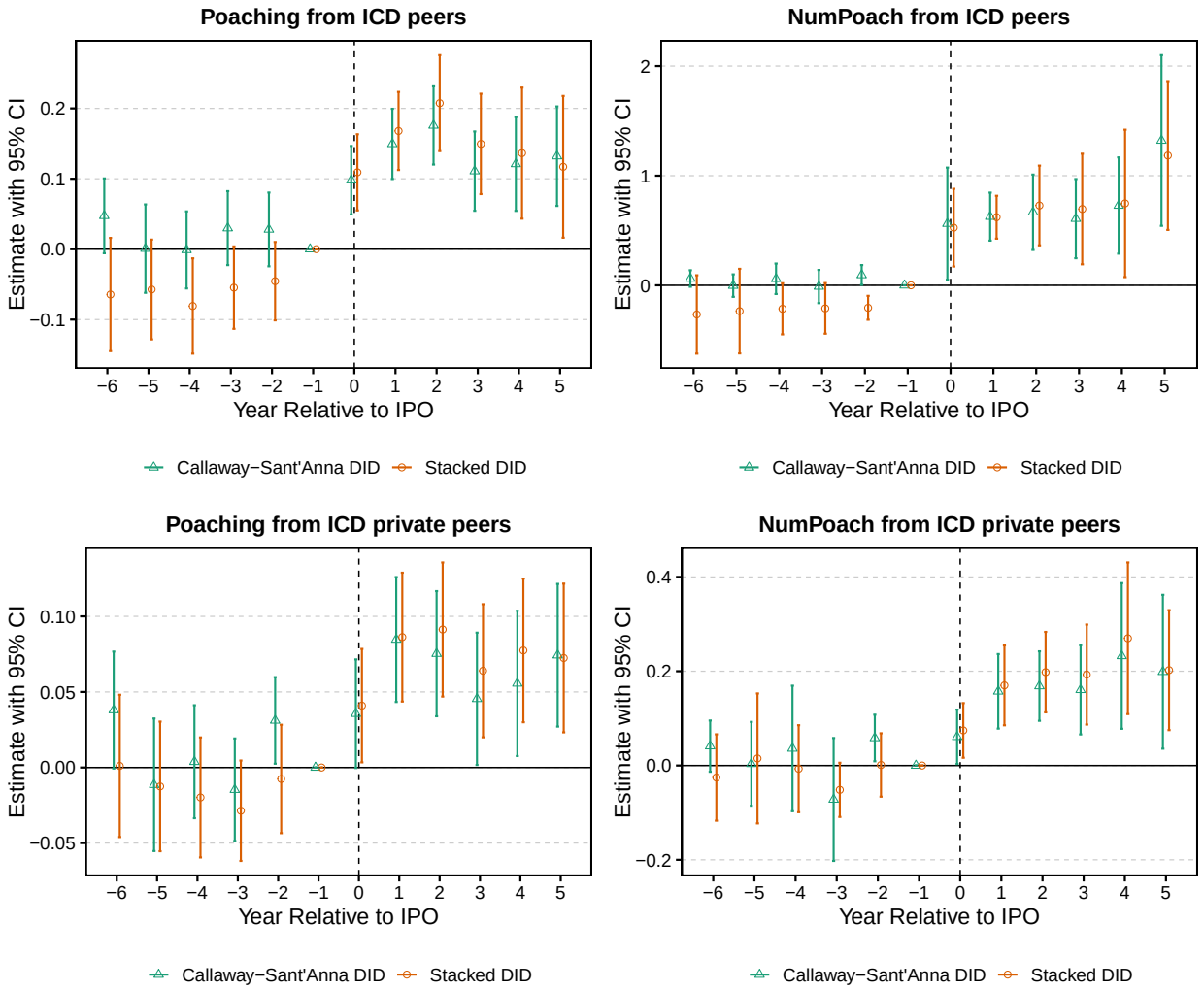

Figure 3: Dynamic Treatment Effects for Worker Exits

This figure plots the dynamic coefficient estimates of *PostIPO* from regression (2), estimated at the worker-year level, for each year surrounding the IPO year (year 0). The outcome variable is *Leave*, an indicator variable that equals one if a worker departs a firm and secures a new job within one year of t, and zero otherwise. This outcome variable is defined separately based on the destination of the worker——whether the employee is leaving to join a peer firm, a public peer firm, or a private peer firm. Error bars represent 95% confidence intervals. Dynamic effects are estimated via a stacked DID methodology (orange plots) or using the methodology of Callaway and Sant'Anna (2021) (green plots). The plotted lines include 95% confidence intervals.

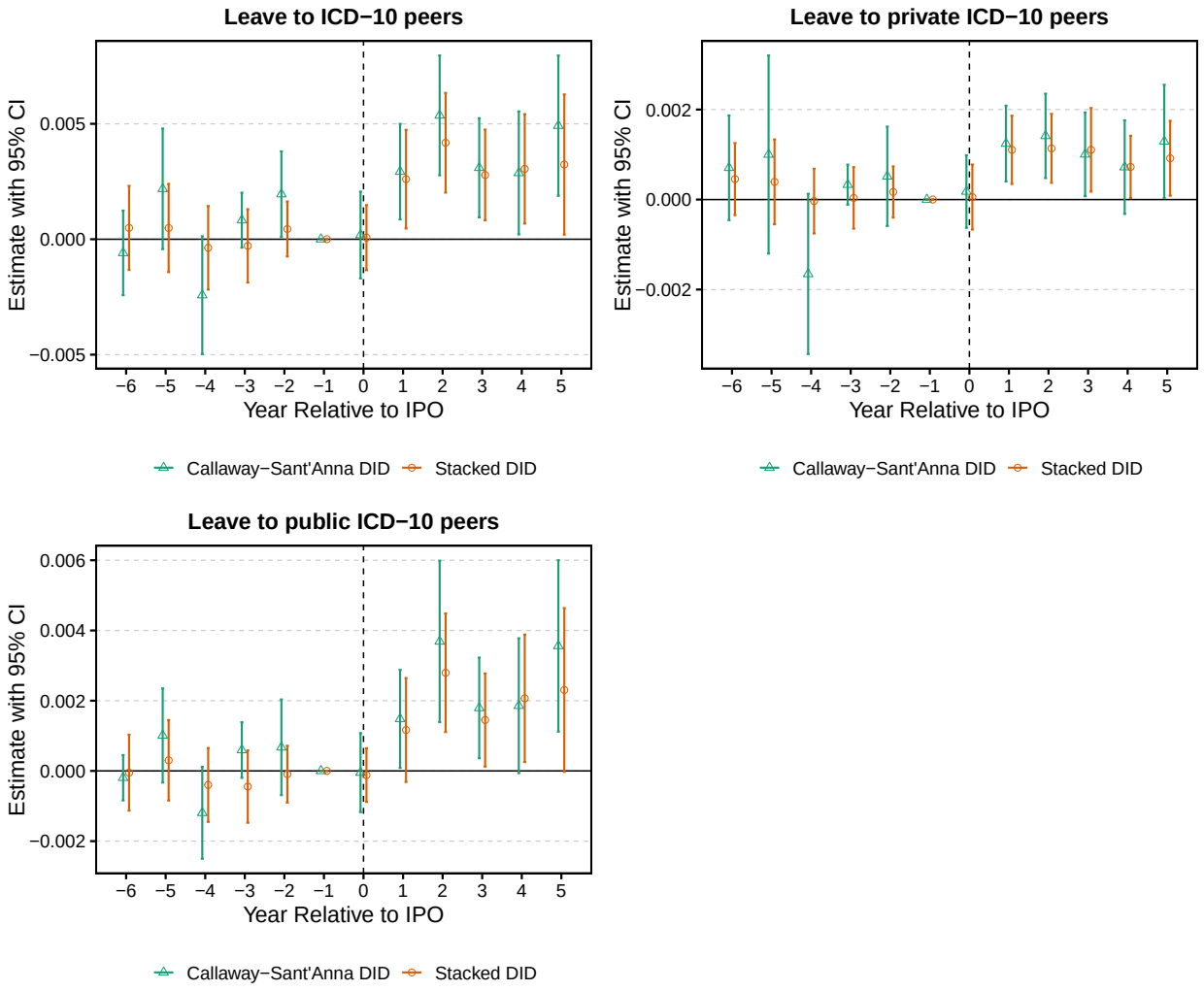

Figure 4: Dynamic Treatment Effects for Innovation Efficiency

This figure plots the dynamic coefficient estimates of $PostIPO$ from regression (2), estimated at the firm-year level, for each year surrounding the IPO year (year 0). The outcome variables are $Progress$, which equals one if the firm has at least one project that advances to the next phase in a given year and zero otherwise, and $Num\,Progress$, the number of projects that advance to the next phase. Error bars represent 95% confidence intervals. Dynamic effects are estimated via a stacked DID methodology (orange plots) or using the methodology of Callaway and Sant'Anna (2021) (green plots). The plotted lines include 95% confidence intervals.

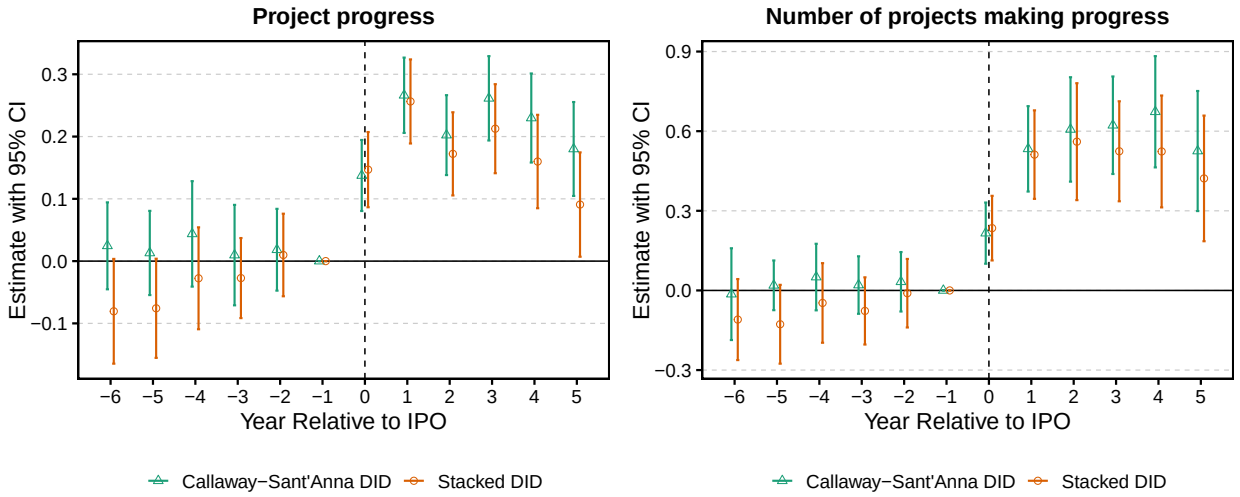

Table 1: Summary Statistics

This table presents summary statistics for the main variables for the stacked sample used in the regression analyses.

Panel A. Sample statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Firm-level sample:						
Poach:						
from all peers	133,080	0.053	0.225	0	0	1
from private peers	130,772	0.021	0.143	0	0	1
NumPoach:						
from all peers	133,080	0.129	1.112	0	0	91
from private peers	130,772	0.038	0.378	0	0	15
PostIPO	130,772	0.017	0.129	0	0	1
Progress	136,863	0.164	0.370	0	0	1
NumProjects	136,863	3.295	3.670	1	2	65
NumProgress	136,863	0.256	0.788	0	0	24
NewProject	136,863	0.515	0.500	0	1	1
NewICD	136,863	0.456	0.498	0	0	1
NewDrug	136,863	0.419	0.493	0	0	1
ProjectApproval	136,863	0.007	0.083	0	0	1
Worker-level sample:						
Leave:						
to all firms	8,007,497	0.034	0.182	0	0	1
to peers	8,007,497	0.002	0.041	0	0	1
to private peers	8,007,497	0.001	0.022	0	0	1
to public peers	8,007,497	0.001	0.032	0	0	1
to startups	8,007,497	0.001	0.029	0	0	1

Panel B. IPO firms versus non-IPO firms

	Non-IPO	IPO	
Statistic		Pre-IPO	Post-IPO
Number of employees (median):			
All employees	8	9	95
Scientists	3	3	19
Clinical Research Associates	0	0	7
Medical Reps	0	0	2
Laboratory Technicians	0	0	5
Project Managers	0	0	1
Number of IPOs		475	

Panel C. Focal firms versus private peers

Statistic	Focal firms	Private peers
Net inflow of workers (mean)	0.013	-0.066
Net inflow of high-experience workers (mean)	0.015	-0.070
Net inflow of low-experience workers (mean)	-0.002	0.004

Table 2: Talent Poaching Following IPOs

This table reports the estimation results for regression (1) examining the effects of IPO on talent poaching. The sample period is from 2000 to 2024. Panel A reports the sample at the firm-year level, and Panel B reports it at the pair-year level. *PostIPO* is an indicator variable that equals one if the firm has undertaken an IPO, and zero otherwise. *Poach* is an indicator variable that equals one if a firm poaches at least one worker from a peer, and zero otherwise. *NumPoach* is the number of employees poached from peers. Standard errors (in parentheses) are clustered at the firm level in Panel A and at the pair level in Panel B. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

Panel A. Firm level

Dependent variable:	*Poach*		*NumPoach*	
	(1) From all peers	(2) From private peers	(3) From all peers	(4) From private peers
PostIPO	0.191***	0.082***	0.854***	0.184***
	(0.018)	(0.012)	(0.165)	(0.040)
Observations	133,080	130,772	133,080	130,772
Y-mean	0.053	0.021	0.129	0.038
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.268	0.183	0.242	0.279

Panel B. Pair level

Dependent variable:	*Poach*		*NumPoach*	
	(1) From ICD-10 peers	(2) From private ICD-10 peers	(3) From ICD-10 peers	(4) From private ICD-10 peers
PostIPO	0.006***	0.003***	0.010***	0.005***
	(0.001)	(0.012)	(0.001)	(0.001)
Observations	6,966,504	4,255,259	6,966,504	4,255,259
Cohort-pair fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	-0.039	0.024	0.132	0.024

Table 3: Talent Poaching from Private Peers Following IPOs by Job Type

This table reports the estimation results for regression (1) examining the effects of IPO on talent poaching from private peers, separated by job title. The sample period is from 2000 to 2024. *PostIPO* is an indicator variable that equals one if the firm has undertaken an IPO, and zero otherwise. *Poach_Title* is an indicator variable that equals one if a firm poaches at least one worker of a given *Title* from a private peer, and zero otherwise. *NumPoach_Title* is the number of employees a given *Title* poached from private peers. Standard errors (in parentheses) are clustered at the firm level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Propensity to Poach

Dependent variable:	*Poach_Scientist*	*Poach_ClinicalRA*	*Poach_LabTechnician*	*Poach_MedicalRep*	*Poach_ProjectManager*
	(1)	(2)	(3)	(4)	(5)
PostIPO	0.036***	0.016***	0.014***	0.003	0.00003
	(0.009)	(0.005)	(0.004)	(0.002)	(0.001)
Observations	130,772	130,772	130,772	130,772	130,772
Y-mean	0.010	0.002	0.002	0.001	0.0003
Cohort-firm fixed effects	Yes	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.125	0.020	-0.033	0.234	-0.177

Panel B. Number of Poaches

Dependent variable:	*NumPoach_Scientist*	*NumPoach_ClinicalRA*	*NumPoach_LabTechnician*	*NumPoach_MedicalRep*	*NumPoach_ProjectManager*
	(1)	(2)	(3)	(4)	(5)
PostIPO	0.054***	0.019***	0.018***	0.003	0.00002
	(0.018)	(0.006)	(0.005)	(0.002)	(0.001)
Observations	130,772	130,772	130,772	130,772	130,772
Y-mean	0.015	0.003	0.002	0.001	0.0003
Cohort-firm fixed effects	Yes	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.254	0.107	-0.045	0.082	-0.169

Table 4: Talent Poaching from Private Peers by Worker/Firm Types

This table reports the estimation results for regression (1) examining the effects of IPO on talent poaching from private peers, separated by either worker or firm type. The sample period is from 2000 to 2024. *PostIPO* is an indicator variable that equals one if the firm has undertaken an IPO, and zero otherwise.*Poach_HighExp* (*Poach_LowExp*) is an indicator variable that equals one if the firm poaches at least one employee with more than three years of experience (less than three years of experience) from its private peers, and zero otherwise. *Poach_LargeEmpSize* (*Poach_SmallEmpSize*) is indicator variable that equals one if the firm hires at least one employee from a private peer that has more (less) employees at the time of poaching, and zero otherwise. *Poach_LargePortSize* (*Poach_SmallPortSize*) is an indicator variable that equals one if the firm hires at least one employee from a private peer that has more (less) projects at the time of poaching, and zero otherwise. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A. High- vs. low-experience

Dependent variable:	*Poach_HighExp*	*Poach_LowExp*	*NumPoach_HighExp*	*NumPoach_LowExp*
	(1)	(2)	(3)	(4)
PostIPO	0.064***	0.038***	0.130***	0.054***
	(0.011)	(0.007)	(0.031)	(0.012)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.017	0.006	0.030	0.008
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.152	0.043	0.248	0.126
Chi-square statistics	2.085**		2.275**	

Panel B. Poaching from larger vs. smaller firms, employee-size

Dependent variable:	*Poach_LargeEmpSize*	*Poach_SmallEmpSize*	*NumPoach_LargeEmpSize*	*NumPoach_SmallEmpSize*
	(1)	(2)	(3)	(4)
PostIPO	0.035***	0.062***	0.055***	0.129***
	(0.009)	(0.009)	(0.019)	(0.032)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.013	0.009	0.023	0.015
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.133	0.102	0.375	0.022
Chi-square statistics	−2.164**		−1.980**	

Panel C. Poaching from larger vs. smaller firms, project portfolio size

Dependent variable:	*Poach_LargePSize*	*Poach_SmallPSize*	*NumPoach_LargePSize*	*NumPoach_SmallPSize*
	(1)	(2)	(3)	(4)
PostIPO	0.027***	0.062***	0.054***	0.130***
	(0.008)	(0.010)	(0.017)	(0.037)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.010	0.012	0.016	0.022
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.139	0.125	0.106	0.335
Chi-square statistics	−2.719***		−1.886*	

Table 5: Heterogeneity in Poaching from Private Peers Following IPOs

This table reports heterogeneity in the effects of IPO on talent poaching by firm size at IPOs. The sample period goes from 2000 to 2024. *Poach* is an indicator variable that equals one if a firm poaches at least one employee from its peers, and zero otherwise. *NumPoach* is the number of employees poached from peers. $PostIPO^{Large\ total\ assets}$ ($PostIPO^{Small\ total\ assets}$) is an indicator variable that equals one if the firm has undertaken an IPO and its total assets in the IPO year are above (below) the median among all IPO firms, and zero otherwise. $PostIPO^{Large\ employee\ size}$ ($PostIPO^{Small\ employee\ size}$) is an indicator variable that equals one if the firm has undertaken an IPO and its total number of workers in the IPO year is above (below) the median among all IPO firms, and zero otherwise. $PostIPO^{Large\ project\ portfolio\ size}$ ($PostIPO^{Small\ project\ portfolio\ size}$) is an indicator variable that equals one if the firm has undertaken an IPO and its total number of projects in the IPO year is above (below) the median among all IPO firms, and zero otherwise. *Poach* is an indicator variable that equals one if a firm poaches at least one employee from its peers, and zero otherwise. *NumPoach* is the number of employees poached from peers. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Dependent variable:	*Poach*			*NumPoach*		
	(1)	(2)	(3)	(4)	(5)	(6)
$PostIPO^{Large\ total\ assets}$	0.122***			0.272***		
	(0.021)			(0.080)		
$PostIPO^{Small\ total\ assets}$	0.050***			0.104***		
	(0.013)			(0.035)		
$PostIPO^{Large\ employee\ size}$		0.102***			0.231***	
		(0.020)			(0.071)	
$PostIPO^{Small\ employee\ size}$		0.058***			0.116***	
		(0.012)			(0.029)	
$PostIPO^{Large\ project\ portfolio\ size}$			0.083***			0.170**
			(0.018)			(0.070)
$PostIPO^{Small\ project\ portfolio\ size}$			0.079***			0.184***
			(0.015)			(0.040)
Observations	130,772	130,772	130,772	130,772	130,772	130,772
Y-mean	0.021	0.021	0.021	0.038	0.038	0.038
Cohort-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.183	0.183	0.182	0.279	0.279	0.279
Chi-square statistic	8.582***	3.665*	0.020	3.803*	2.312	0.032

Table 6: Worker Exits Following IPOs

This table reports worker-level results for regression (2) examining the effects of IPOs on worker exits. *Leave* is an indicator variable that equals one if a worker departs the focal firm and secures a new job within one year of departure, and zero otherwise. $PostIPO$ is an indicator variable that equals one if the firm has undertaken an IPO, and zero otherwise. Standard errors are clustered at the firm level and are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Dependent variable:	*Leave*			
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
PostIPO	0.003***	0.001***	0.002***	0.00004
	(0.001)	(0.0003)	(0.001)	(0.0002)
Observations	8,007,497	8,007,497	8,007,497	8,007,497
Y-mean	0.002	0.001	0.001	0.001
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.012	0.012	0.017

Table 7: Heterogeneity in Worker Exits Following IPOs

This table reports worker-level regression results examining heterogeneity in the effects of IPOs on incumbent exits. *Leave* is an indicator variable that equals one if a worker departs the focal firm and secures a new job within one year of departure, and zero otherwise. *LowExp* is an indicator variable that equals one if a worker has fewer than three years of experience at the time of departure, and zero otherwise. *LowSalary* is an indicator variable that equals one if a worker's salary is below the median salary of employees in the same rank within the same company–year, and zero otherwise. *TopLeader* is an indicator variable that equals one if the worker is a top leader at the time of departure, and zero otherwise. *Female* is an indicator variable that equals one if the worker is female, and zero otherwise. *PhD* is an indicator variable that equals one if the worker holds a Ph.D. degree, and zero otherwise. *Scientist* is an indicator variable that equals one if the worker takes a scientist role at the time of departure, and zero otherwise. Standard errors are clustered at the firm level and are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Dependent variable:				*Leave*			
Destination:				Private peers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PostIPO	0.001**	0.001***	0.001***	0.001***	0.001**	0.001**	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
PostIPO × *LowExp*	0.0004*						0.0004**
	(0.0002)						(0.0002)
PostIPO × *LowSalary*		0.0001					0.0002
		(0.0002)					(0.0002)
PostIPO × *TopLeader*			0.001*				0.001
			(0.0004)				(0.0004)
PostIPO × *Female*				-0.0004**			-0.0004**
				(0.0002)			(0.0002)
PostIPO × *PhD*					0.001***		0.001***
					(0.0003)		(0.0003)
PostIPO × *Scientist*						0.001*	0.0004
						(0.0003)	(0.0003)
LowExp	0.0002**						0.0002*
	(0.0001)						(0.0001)
LowSalary		0.0002***					0.0003***
		(0.0001)					(0.0001)
TopLeader			-0.0002**				-0.0002**
			(0.0001)				(0.0001)
Female				0.0001			0.0001
				(0.0001)			(0.0001)
PhD					0.0004**		0.0003**
					(0.0002)		(0.0002)
Scientist						0.0005***	0.0004**
						(0.0002)	(0.0002)
Observations	8,074,739	8,074,692	8,074,739	8,074,739	8,074,739	8,074,739	8,074,692
Y-mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Cohort-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.012	0.012	0.012	0.012	0.012	0.012	0.012

Table 8: Innovation Efficiency Following IPOs

This table reports the regression results examining the effects of IPOs on innovation efficiency. $PostIPO$ is an indicator variable that equals one if the firm has undertaken an IPO, and zero otherwise. $Progress$ is defined at two levels. At the project level, $Progress$ equals one if the project advances to the next development phase in year t, and zero otherwise. At the firm level, $Progress$ equals one if the firm has at least one project that advances to the next phase in year t, and zero otherwise. $NumProgress$ is the number of projects that advance to the next phase. Standard errors are clustered at the firm level and are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Dependent variable:	*Progress*			*NumProgress*
	Firm-level	Project-level	Project-level	Firm-level
	(1)	(2)	(3)	(4)
PostIPO	0.148***	0.017**	0.016*	0.379***
	(0.018)	(0.007)	(0.009)	(0.047)
Observations	136,863	451,020	451,020	136,863
Y-mean	0.164	0.078	0.078	0.256
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
ICD-10 fixed effects	-	Yes	No	-
Drug fixed effects	No	No	Yes	No
Firm Portfolio Size Control	Yes	-	-	Yes
Adjusted R^2	0.105	0.091	0.196	0.154

Table 9: Innovation Following Talent Reallocation Since IPOs

This table reports the firm-level results for regression (3) examining the effects of worker flows following IPOs on innovation efficiency. *Progress* equals one if the firm has at least one project that advances to the next phase in year t, and zero otherwise. $NumProgress$ is the number of projects that advance to the next phase. *Net Poach IPO* is the cumulative net number of employees that a firm has poached from its private peers as of a given year, defined as the number of workers packed from private peers minus the number of workers that left the IPO firm to go to private peers. $Net\,Poach\,IPO^{High\,Exp}$ ($Net\,Poach\,IPO^{Low\,Exp}$) is *Net Poach IPO* restricted to employees with more (less) than three years of experience. Standard errors are clustered at the firm level and show in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Dependent variable:	*Progress*		*NumProgress*	
	(1)	(2)	(3)	(4)
Net Poach IPO	0.010**		0.113*	
	(0.005)		(0.006)	
$Net\,Poach\,IPO^{High\,Exp}$		0.018**		0.219***
		(0.008)		(0.079)
$Net\,Poach\,IPO^{Low\,Exp}$		−0.003		−0.068
		(0.015)		(0.053)
Observations	136,863	136,863	136,863	136,863
Y-mean	0.164	0.164	0.256	0.256
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Firm Portfolio Size Control	Yes	Yes	Yes	Yes
Adjusted R^2	0.104	0.104	0.155	0.154

Table 10: Private Firms Innovation Following Peers' IPOs

This table reports firm-year level regression results examining the effects of peer IPOs on private firms' innovation efficiency. The sample includes private (never-IPO) firms from 2000 to 2024. *Progress* is a project-level indicator that equals one if the project progresses into the next phase in year t, and zero otherwise. *NumProgress* is the number of projects advancing to the next phase. $PeerIPO_{[t-1,t-3]}$ is an indicator variable that equals one if the private firm has at least one peer firm that had an IPO in the past 3 years, and zero otherwise. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A. Private Peer Innovation

Dependent variable:	*Progress*	*NumProgress*
	Project-level	Firm-level
	(1)	(2)
$PeerIPO_{[t-3,t-1]}$	−0.014**	−0.056**
	(0.006)	(0.008)
Observations	39,483	15,759
Y-mean	0.085	0.394
Firm fixed effects	Yes	Yes
ICD-10 fixed effects	Yes	-
Year fixed effects	Yes	Yes
Firm Portfolio Size Control	-	Yes
Adjusted R^2	0.083	0.236

Panel B. Heterogeneity in Private Peer Innovation based on Poaching

Dependent variable:	*Progress*		*NumProgress*	
	Project-level		Firm-level	
	(1)	(2)	(3)	(4)
$PeerIPO_{[t-3,t-1]}$	−0.014**	−0.013*	−0.057**	−0.052**
	(0.006)	(0.006)	(0.026)	(0.026)
$PeerIPO_{[t-3,t-1]} \times In\,Migration_{[t-3,t-1]}$	0.001		0.016	
	(0.003)		(0.019)	
$PeerIPO_{[t-3,t-1]} \times Out\,Migration_{[t-3,t-1]}$	−0.001		0.004	
	(0.002)		(0.013)	
$PeerIPO_{[t-3,t-1]} \times In\,Migration^{High\,Exp}_{[t-3,t-1]}$		−0.021		−0.041
		(0.019)		(0.064)
$PeerIPO_{[t-3,t-1]} \times In\,Migration^{Low\,Exp}_{[t-3,t-1]}$		0.002		0.014
		(0.002)		(0.019)
$PeerIPO_{[t-3,t-1]} \times Out\,Migration^{High\,Exp}_{[t-3,t-1]}$		−0.009**		−0.011
		(0.004)		(0.034)
$PeerIPO_{[t-3,t-1]} \times Out\,Migration^{Low\,Exp}_{[t-3,t-1]}$		0.012**		0.033
		(0.006)		(0.042)
Observations	39,483	39,483	15,759	15,759
Y-mean	0.085	0.085	0.394	0.394
Firm fixed effects	Yes	Yes	Yes	Yes
ICD-10 fixed effects	Yes	Yes	-	-
Year fixed effects	Yes	Yes	Yes	Yes
Firm Portfolio Size Control	-	-	Yes	Yes
Adjusted R^2	0.083	0.083	0.238	0.239

Table 11: Private Firms' Innovation Efficiency Following Peers' IPOs by Private Firm Size

This table reports the firm-year regression results examining the effects of peer IPOs on private firms' innovation efficiency split by size. The sample includes private (never-IPO) firms from 2000 to 2024. *Progress* is a project-level indicator that equals one if the project progresses into the next phase in year t, and zero otherwise. $NumProgress$ is the number of projects advancing to the next phase. $PeerIPO_{[t-3,t-1]}$ is an indicator variable that equals one if the private firm has at least one peer firm that had an IPO in the past 3 years, and zero otherwise. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A. Private Peer Innovation

Dependent variable:	*Progress*		*NumProgress*	
	Project-level		Firm-level	
	(1)	(2)	(3)	(4)
$PeerIPO_{[t-3,t-1]}$	−0.005	−0.023**	−0.056	−0.066*
	(0.009)	(0.010)	(0.048)	(0.036)
Sample	Large scientist-size	Small scientist-size	Large scientist-size	Small scientist-size
Observations	21,378	18,105	8,242	7,517
Y-mean	0.082	0.089	0.467	0.314
Firm fixed effects	Yes	Yes	Yes	Yes
ICD-10 fixed effects	Yes	Yes	-	-
Year fixed effects	Yes	Yes	Yes	Yes
Firm Portfolio Size Control	-	-	Yes	Yes
Adjusted R^2	0.079	0.105	0.248	0.263
Chi-square statistic	1.361		0.165	

Panel B. Heterogeneity in Private Peer Innovation based on Poaching

Dependent variable:	*Progress*		*NumProgress*	
	Project-level		Firm-level	
	(1)	(2)	(3)	(4)
$PeerIPO_{[t-3,t-1]}$	−0.003	−0.022**	−0.062	−0.050
	(0.009)	(0.010)	(0.048)	(0.032)
$PeerIPO_{[t-3,t-1]} \times In\,Migration^{High\,Exp}_{[t-3,t-1]}$	−0.016	0.163***	−0.024	−0.150
	(0.017)	(0.028)	(0.063)	(0.240)
$PeerIPO_{[t-3,t-1]} \times In\,Migration^{Low\,Exp}_{[t-3,t-1]}$	0.003	0.056	0.021	0.136
	(0.002)	(0.038)	(0.015)	(0.298)
$PeerIPO_{[t-3,t-1]} \times Out\,Migration^{High\,Exp}_{[t-3,t-1]}$	−0.006	−0.023***	0.019	−0.073*
	(0.008)	(0.007)	(0.038)	(0.037)
$PeerIPO_{[t-3,t-1]} \times Out\,Migration^{Low\,Exp}_{[t-3,t-1]}$	0.008	0.062	−0.001	−0.036
	(0.011)	(0.047)	(0.047)	(0.107)
Sample	Large scientist-size	Small scientist-size	Large scientist-size	Small scientist-size
Observations	21,378	18,105	8,242	7,517
Y-mean	0.082	0.089	0.467	0.314
Firm fixed effects	Yes	Yes	Yes	Yes
ICD-10 fixed effects	Yes	Yes	-	-
Year fixed effects	Yes	Yes	Yes	Yes
Firm Portfolio Size Control	-	-	Yes	Yes
Adjusted R^2	0.079	0.106	0.253	0.273

Appendix

A Variable description

Variable name	Description
IPO:	
$PostIPO$	An indicator variable that equals one if a firm has undertaken an IPO, and zero otherwise.
$PostIPO^{Large\ total\ assets}$	An indicator variable that equals one if a firm has undertaken an IPO and its total assets in the IPO year are above the median among all IPO firms, and zero otherwise.
$PostIPO^{Small\ total\ assets}$	An indicator variable that equals one if a firm has undertaken an IPO and its total assets in the IPO year are below the median among all IPO firms, and zero otherwise.
$PostIPO^{High\ num\ of\ workers}$	An indicator variable that equals one if a firm has undertaken an IPO and its total number of workers in the IPO year is above the median among all IPO firms, and zero otherwise.
$PostIPO^{Low\ num\ of\ workers}$	An indicator variable that equals one if a firm has undertaken an IPO and its total number of workers in the IPO year is below the median among all IPO firms, and zero otherwise.
$PostIPO^{Large\ project\ portfolio}$	An indicator variable that equals one if a firm has undertaken an IPO and its total number of projects in the IPO year is above the median among all IPO firms, and zero otherwise.
$PostIPO^{Small\ project\ portfolio}$	An indicator variable that equals one if a firm has undertaken an IPO and its total number of projects in the IPO year is below the median among all IPO firms, and zero otherwise.
$PeerIPO$	An indicator variable that equals one if the private firm has at least one peer firm that had an IPO in the past n years, and zero otherwise.
Talent poaching:	
Poach	An indicator variable that equals one if a firm poaches at least one employee, and zero otherwise.
Poach_HighExp	An indicator variable that equals one if a firm poaches at least one high-experience employee ($\geq$ 3-year experience) from its private peers, and zero otherwise.
Poach_LowExp	An indicator variable that equals one if a firm poaches at least one low-experience employee ($<$ 3-year experience) from its private peers, and zero otherwise.
Poach_PhD	An indicator variable that equals one if a firm poaches at least one Ph.D. holder from its private peers, and zero otherwise.
Poach_NonPhD	An indicator variable that equals one if a firm poaches at least one non-Ph.D. holder from its private peers, and zero otherwise.
Poach_Top	An indicator variable that equals one if a firm poaches at least one top leader from its private peers, and zero otherwise.

Poach_NonTop	An indicator variable that equals one if a firm poaches at least one non-top leader from its private peers, and zero otherwise.
Poach_InState	An indicator variable that equals one if a firm poaches at least one employee from its private peers in the same state, and zero otherwise.
Poach_OutofState	An indicator variable that equals one if a firm poaches at least one employee from its private peers in a different state, and zero otherwise.
Poach_LargeEmpSize	An indicator variable that equals one if the firm hires at least one employee from a private peer that has more employees at the time of poaching, and zero otherwise.
Poach_SmallEmpSize	An indicator variable that equals one if the firm hires at least one employee from a private peer that has fewer employees at the time of poaching, and zero otherwise.
Poach_LargePSize	An indicator variable that equals one if the firm hires at least one employee from a private peer that has more projects at the time of poaching, and zero otherwise.
Poach_SmallPSize	An indicator variable that equals one if the firm hires at least one employee from a private peer that has fewer projects at the time of poaching, and zero otherwise.
Net Poach IPO	The difference between the cumulative number of workers a firm has poached from its private peers and the cumulative number of employees who leave the firm to join private-peer firms, from the IPO year through year t.
Net Poach IPO_HighExp	The difference between the cumulative number of high-experience workers a firm has poached from its private peers and the cumulative number of high-experience employees who leave the firm to join private-peer firms, from the IPO year through year t.
Net Poach IPO_LowExp	The difference between the cumulative number of low-experience workers a firm has poached from its private peers and the cumulative number of low-experience employees who leave the firm to join private-peer firms, from the IPO year through year t.
In Migration	The number of workers who migrated into the private firms from IPO peers in the past n years.
In Migration_HighExp	The number of high-experience workers who migrated into the private firms from IPO peers in the past n years.
In Migration_LowExp	The number of low-experience workers who migrated into the private firms from IPO peers in the past n years.
Out Migration	The number of workers who migrated out of the private firms to IPO peers in the past n years.
Out Migration_HighExp	The number of high-experience workers who migrated out of the private firms to IPO peers in the past n years.
Out Migration_LowExp	The number of low-experience workers who migrated out of the private firms to IPO peers in the past n years.
Innovation efficiency:	
Progress	An project-level indicator that equals one if the project advances to the next development phase in year t, and zero otherwise; or a firm-level indicator that equals one if the firm has at least one project that advances to the next phase in year t, and zero otherwise.

NumProgress	The number of projects that advance to the next phase.
Worker-level variable:	
Leave	An indicator variable that equals one if the incumbent departs the focal firm and secures a new job within one year of departure, and zero otherwise.
LowExp	An indicator variable that equals one if a worker has fewer than three years of experience at the time of departure, and zero otherwise.
LowSalary	An indicator variable that equals one if a worker's salary is below the median salary of employees in the same rank within the same company–year, and zero otherwise.
TopLeader	An indicator variable that equals one if the worker is a top leader at the time of departure, and zero otherwise.
Female	An indicator variable that equals one if the worker is female, and zero otherwise.
PhD	An indicator variable that equals one if the worker holds a Ph.D. degree, and zero otherwise.
Other variable:	
NumProjects	The number of active projects in a firm's drug pipeline.

B Matching procedure

We construct a sample of pharmaceutical development projects initiated by U.S.-based companies that can be matched to firm-level employment records from Revelio Labs. Given that the two databases share no common firm identifiers, we implement an iterative fuzzy name-matching procedure to maximize the matching rate.

We begin with 106,876 unique firms from Cortellis and merge this dataset with the Revelio Labs company file, which contains approximately 24 million unique firms. First, we use the GPT-4.1 model to identify 91,643 for-profit firms within the Cortellis data. Next, we perform fuzzy matching on for-profit firm names between Cortellis and Revelio Labs. To harmonize company names, we remove punctuation, strip trailing incorporation designators (e.g., "Inc," "LLC"), and correct obvious typographical errors.

The matching process is conducted iteratively in two stages. In the first stage, we apply exact matching to identify identical firm names, remove these matched pairs, and then apply fuzzy matching with a 95% similarity threshold to the remaining firms, yielding a 61.5% match rate among for-profit firms. In the second stage, we lower the threshold to 90% to capture additional variations, accepting a higher tolerance for potential false positives. For firms still unmatched, we use GPT-4.1 to infer former or alternative names and reapply the exact and fuzzy matching steps. This procedure produces an overall match rate of 83.5% among for-profit Cortellis firms.

As a final quality check, we use GPT-4.1 to review all matched pairs and discard those identified as mismatches. The resulting matched sample includes 59,054 Cortellis firms linked to Revelio Labs, representing a 64.4% final match rate.

Table A.1: Talent Poaching from Private Peers by Worker/Firm Types

This table reports the estimation results for regression (1) examining the effects of IPO on talent poaching from private peers, separated by either worker or firm type. The sample period is from 2000 to 2024. *PostIPO* is an indicator variable that equals one if the firm has undertaken an IPO, and zero otherwise. *Poach_PhD* (*Poach_NonPhD*) is an indicator variable that equals one if the firm poaches at least one Ph.D. holder (non-Ph.D. holder) from its private peers, and zero otherwise. *Poach_Top* (*Poach_NonTop*) is an indicator variable that equals one if the firm poaches at least one top leader (non-top leader) from its private peers, and zero otherwise. *Poach_InState* (*Poach_OutofState*) is an indicator variable that equals one if the firm poaches at least one employee from its private peers in the same state (a different state), and zero otherwise. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A. Ph.D vs. Non-PhD holders

Dependent variable:	*Poach_PhD*	*Poach_NonPhD*	*NumPoach_PhD*	*NumPoach_NonPhD*
	(1)	(2)	(3)	(4)
PostIPO	0.048***	0.064***	0.071***	0.124***
	(0.009)	(0.011)	(0.018)	(0.028)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.010	0.017	0.013	0.027
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.121	0.146	0.277	0.182
Chi-square statistics	-1.121		-1.620	

Panel B. Top leaders vs. Non-top leaders

Dependent variable:	*Poach_Top*	*Poach_NonTop*	*NumPoach_Top*	*NumPoach_NonTop*
	(1)	(2)	(3)	(4)
PostIPO	0.013***	0.075***	0.018***	0.166***
	(0.005)	(0.012)	(0.006)	(0.037)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.002	0.020	0.002	0.036
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.177	0.171	0.216	0.249
Chi-square statistics	-4.905***		-3.933***	

Panel C. In-state vs. Out-of-state

Dependent variable:	*Poach_InState*	*Poach_OutofState*	*NumPoach_InState*	*NumPoach_OutofState*
	(1)	(2)	(3)	(4)
PostIPO	0.073***	0.030***	0.143***	0.041***
	(0.011)	(0.007)	(0.034)	(0.010)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.010	0.011	0.020	0.018
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
S.E. Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.201	-0.021	0.306	-0.009
Chi-square statistics	3.258***		2.907***	

Panel D. Larger vs. smaller scientist-size

Dependent variable:	*Poach_LargeScientistSize*	*Poach_SmallScientistSize*	*NumPoach_LargeScientistSize*	*NumPoach_SmallScientistSize*
	(1)	(2)	(3)	(4)
PostIPO	0.036***	0.059***	0.052***	0.131***
	(0.009)	(0.009)	(0.019)	(0.032)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.012	0.010	0.021	0.016
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.130	0.105	0.367	0.090
Chi-square statistics	-1.763*		-2.025**	

Panel E. High vs. low-experience scientist

Dependent variable:	*Poach_Scientist_HighExp*	*Poach_Scientist_LowExp*	*NumPoach_Scientist_HighExp*	*NumPoach_Scientist_LowExp*
	(1)	(2)	(3)	(4)
PostIPO	0.023***	0.019***	0.033**	0.021***
	(0.008)	(0.005)	(0.014)	(0.006)
Observations	130,772	130,772	130,772	130,772
Y-mean	0.008	0.003	0.011	0.003
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.112	0.008	0.291	0.048
Chi-square statistics	0.376		0.748	

Panel F. Seniority rank of scientists

Dependent variable:	*Poach_Scientist_Junior*	*Poach_Scientist_Senior*	*Poach_Scientist_TopLeader*	*NumPoach_Scientist_Junior*	*NumPoach_Scientist_Senior*	*NumPoach_Scientist_TopLeader*
	(1)	(2)	(3)	(4)	(5)	(6)
PostIPO	0.021***	0.018***	0.005*	0.020*	0.029***	0.005*
	(0.007)	(0.006)	(0.003)	(0.011)	(0.008)	(0.003)
Observations	130,772	130,772	130,772	130,772	130,772	130,772
Y-mean	0.006	0.004	0.001	0.008	0.006	0.001
Cohort-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.075	0.100	0.166	0.066	0.387	0.166

Table A.2: Heterogeneity in Worker Exits Following IPOs

This table reports the worker-level regression results examining heterogeneity in the effects of IPOs on incumbent exits by firm size. ***, **, and * represent significance at the 1%, 5%, and 10% levels.

Panel A. Worker exits split by total assets of IPO Firms

Dependent variable:	*Leave*			
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
$PostIPO^{Large\ total\ assets}$	0.007***	0.001***	0.005***	0.00001
	(0.001)	(0.0003)	(0.001)	(0.0003)
$PostIPO^{Small\ total\ assets}$	0.005***	0.002**	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	8,074,692	8,074,692	8,074,692	8,074,692
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.012	0.012	0.017
Chi-square statistic	1.995	0.107	4.964**	0.740

Panel B. Worker exits split by number of workers at IPO Firms

Dependent variable:	*Leave*			
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
$PostIPO^{High\ num\ of\ workers}$	0.003**	0.001**	0.002**	0.0001
	(0.001)	(0.0004)	(0.001)	(0.0002)
$PostIPO^{Low\ num\ of\ workers}$	0.005***	0.001	0.004***	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	8,074,692	8,074,692	8,074,692	8,074,692
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.012	0.012	0.017
Chi-square statistic	1.733	0.0001	1.240	0.007

Panel C. Worker exits by project portfolio size of IPO Firms

Dependent variable:	*Leave*			
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
$PostIPO^{Large\ project\ portfolio}$	0.007***	0.002***	0.005***	−0.0001
	(0.001)	(0.001)	(0.001)	(0.0004)
$PostIPO^{Small\ project\ portfolio}$	0.001	0.0004	0.001	0.0001
	(0.001)	(0.0003)	(0.001)	(0.0002)
Observations	8,074,692	8,074,692	8,074,692	8,074,692
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.012	0.012	0.017
Chi-square statistic	16.470***	4.680**	19.876***	0.185

Table A.3: Worker Exits Across Different Timeframes

This table reports results from worker-level regression (2) examining the effect of IPOs on worker exits. *Leave* is an indicator variable that equals one if a worker departs from the firm and secures a new job within the specified timeframe, and zero otherwise Standard errors are clustered at the firm level and shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A. Within 6-months

Dependent variable:			*Leave*	
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
PostIPO	0.002***	0.001***	0.002***	−0.00004
	(0.001)	(0.0003)	(0.001)	(0.0001)
Observations	7,818,461	7,818,461	7,818,461	7,818,461
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.019	0.014	0.013	0.016

Panel B. Within 2-year

Dependent variable:			*Leave*	
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
PostIPO	0.003***	0.001***	0.002***	0.00003
	(0.001)	(0.0003)	(0.001)	(0.0002)
Observations	8,207,847	8,207,847	8,207,847	8,207,847
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.015	0.007	0.011	0.018

Panel C. Within 3-year

Dependent variable:			*Leave*	
Destination:	All peers	Private peers	Public peers	Startups
	(1)	(2)	(3)	(4)
PostIPO	0.003***	0.001***	0.002**	0.00005
	(0.001)	(0.0003)	(0.001)	(0.0002)
Observations	8,362,805	8,362,805	8,362,805	8,362,805
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.014	0.006	0.010	0.017

Table A.4: Other Innovation Outcomes Following IPOs

This table reports the firm-level regression results examining the effect of IPOs on other innovation outcomes. Standard errors are clustered at the firm level and shown in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels.

Panel A. Innovation outcomes following IPOs

Dependent variable:	*NewProject*	*NewICD*	*NewDrug*	*ProjectApproved*
	(1)	(2)	(3)	(4)
PostIPO	0.113***	0.088***	0.074***	0.020***
	(0.020)	(0.020)	(0.020)	(0.005)
Observations	136,863	136,863	136,863	136,863
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.182	0.172	0.184	0.117

Panel B. Innovation outcomes following IPOs, heterogeneity by experience of poached workers

Dependent variable:	*NewProject*		*NewICD*		*NewDrug*		*ProjectApproved*	
	(1)	(2)	(3)	(4)				
Net Poach IPO_HighExp	0.022**		0.020*		0.027**		0.006	
	(0.010)		(0.011)		(0.013)		(0.004)	
Net Poach IPO_LowExp	0.029**		0.023		0.025*		−0.001	
	(0.014)		(0.015)		(0.015)		(0.005)	
Total Poach IPO_HighExp		0.003		0.015		0.012		0.003
		(0.013)		(0.015)		(0.017)		(0.006)
Total Poach IPO_LowExp		0.064***		0.037*		0.056***		0.006
		(0.018)		(0.020)		(0.020)		(0.008)
Total Exit IPO_HighExp		−0.033**		−0.006		−0.023		−0.002
		(0.015)		(0.016)		(0.020)		(0.006)
Total Exit IPO_LowExp		0.006		−0.010		0.005		0.006
		(0.017)		(0.019)		(0.020)		(0.007)
Observations	136,863	136,863	136,863	136,863	136,863	136,863	136,863	136,863
Cohort-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.182	0.182	0.182	0.182	0.184	0.184	0.117	0.117

Table A.5: Innovation Efficiency Following Talent Reallocation Since IPOs

This table reports the firm-level regression results examining the effects of IPO on innovation efficiency. *Progress* equals one if the firm has at least one project that advances to the next phase in year t, and zero otherwise. *NumProgress* is the number of projects that advance to the next phase. *Total_Poach_IPO* is the cumulative number of workers a firm has poached from its private peers from the IPO year through year t. *Total_Leave_IPO* is the cumulative number of employees who leave the firm to join private-peer firms from the IPO year through year t. *Total_Poach_HighExp* (*Cusum_Poach_LowExp*) is the cumulative number of workers with more than (less than) three years of experience that a firm has poached from its private peers from the IPO year through year t. *Total_Leave_HighExp* (*Cusum_Leave_LowExp*) is the cumulative number of employees with more than (less than) three years of experience who leave the firm to join private-peer firms from the IPO year through year t. Standard errors are clustered at the firm level and shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Dependent variable:	*Progress*		*NumProgress*	
	(1)	(2)	(3)	(4)
Total_Poach_IPO	0.027***		0.204***	
	(0.010)		(0.028)	
Total_Leave_IPO	0.00000		0.0001	
	(0.00002)		(0.0001)	
Total_Poach_IPO_HighExp		0.017		0.187***
		(0.016)		(0.051)
Total_Poach_IPO_LowExp		0.029		0.158**
		(0.019)		(0.063)
Total_Leave_IPO_HighExp		0.003		0.053
		(0.020)		(0.083)
Total_Leave_IPO_LowExp		0.027		0.129*
		(0.019)		(0.070)
Observations	136,863	136,863	136,863	136,863
Y-mean	0.164	0.164	0.256	0.256
Cohort-firm fixed effects	Yes	Yes	Yes	Yes
Cohort-year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.074	0.075	0.122	0.124