# From Private to Public: Pharmaceutical R&D and Hiring Patterns Post-IPO*

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**Abstract**

This paper investigates the impact of public financial markets on firms' innovation decisions and hiring flows. In the biopharmaceutical sector—where smaller, financially constrained firms invest in risky projects with long development timelines—an initial public offering (IPO) can enable access to necessary financial capital and act as a signal of quality to potential employees. Using detailed project-level data on drug development, we find that going public increases both the level and quality of firms' research activity across clinical trial stages; however, the additional R&D is concentrated in disease areas already represented in firms' pipelines. Linking our sample of US pharmaceutical firms to comprehensive workforce data, we find that firms completing IPOs substantially grow their labor forces, through both incumbent retention and greater hiring of experienced employees. Our results suggest that IPOs bring increased external scrutiny, leading firms to engage in lower-risk activities, while also relaxing financing and human capital constraints so that firms may pursue additional R&D efforts.

**Keywords**: Initial Public Offerings; Corporate Innovation; Research and Development; Pharmaceutical Industry; Labor Markets

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## 1 Introduction

It is well-established that in capital-intensive industries, public financial markets play an important role in firms' innovative incentives (Brown et al., 2009; Hsu et al., 2014; Kerr and Nanda, 2015; Levine, 1997). Access to public equity markets and associated resources can enable financially constrained, less experienced firms to expand their innovative activities (Brau and Fawcett, 2006; Hall and Lerner, 2010). At the same time, public ownership may hinder innovative productivity by exacerbating agency conflicts, reducing managerial risk tolerance, fostering short-termism, or causing organizational changes (Berle and Means, 1932; Holmström, 1989, 1999; Meckling and Jensen, 1976; Stein, 1989; Stuart and Sorenson, 2003). The coexistence of these financing benefits and governance frictions leaves the net effect of going public on innovation theoretically ambiguous.

A large empirical literature has examined this trade-off in cross-industry studies by examining how public markets shape patenting, an early-stage measure of research effort. In general, researchers have found that going public is associated with no change or an aggregate decline in subsequent patenting activity (e.g., Bernstein, 2015; Dambra and Gustafson, 2021). However, a growing literature shows that external financing needs can vary across industries (Acharya and Xu, 2017; Rajan and Zingales, 1998) and that firm patenting may not be an accurate proxy for firm-level investments in innovation (Higham et al., 2021; Lerner and Seru, 2021; Moser, 2016). In addition, these aggregate patenting measures may mask significant heterogeneity in the response across different types of R&D investments.

Our paper revisits this trade-off by focusing on R&D outcomes and hiring patterns in the biopharmaceutical industry, a setting where firms seeking to bring new products to market must navigate long development times and substantial regulatory uncertainties. These features make access to key resources, such as capital, collaborators, and skilled personnel, especially important. We exploit unique features of the setting to examine the effects of going public on the quantity, composition, and quality of subsequent innovation. In particular, by leveraging detailed data on a firm's drug development portfolio, we construct granular measures of innovative activity that may not be apparent from patenting data. Further, by linking these firms to comprehensive person-level employment records, we explore hiring patterns as firms transition to public markets and how they may underlie the innovation outcomes we observe.

We find that IPOs have important impacts to pharmaceutical firms' R&D decisions. We observe increased research activity across the development process for firms with completed IPOs relative to those without. In particular, an IPO increases the likelihood that a firm initiates any clinical research investment by 46 percent. Examining how firms shift the direction of their innovative activity, we find that, following an IPO, firms are more likely to expand research efforts in diseases

already in their R&D pipelines rather than explore different disease categories or pursue novel mechanisms of action. We also find evidence of higher-quality clinical trials post-IPO.

To understand the drivers behind the increased research activity we observe post-IPO, we examine changes to firms' hiring patterns. We find that firms that go public grow their labor forces substantially relative to their private counterparts, both overall and across scientific, regulatory, commercial, and operations job categories. Further, we demonstrate that firms with completed IPOs have higher incumbent retention and new employee hiring rates, with the greatest increases in hiring among more experienced employees. These results are consistent with the hypothesis that an IPO increases the financial resources and publicity that enable firms to expand their workforces after an IPO. Combined, our results point to competing mechanisms underlying the potential impact of an IPO on product development: The transition to public ownership brings increased external scrutiny, leading firms to engage in lower-risk activities, but also provides firms with needed resources, especially human capital, to pursue R&D efforts.

Our data and setting allow us to make two main contributions to the existing literature. First, we use detailed Cortellis data tracking clinical trial outcomes throughout the drug development process to examine innovation outcomes. With these data, we are able to create more precise measures of product direction and progress following an IPO than available via traditional patent measures. Second, by matching our sample of analytic firms to comprehensive workforce data from Revelio Labs, we can follow workers over time in and out of our sample, determining hiring flows for firms that transition to public ownership and how those hiring patterns contribute to R&D outcomes.

The paper proceeds as follows: Section 2 gives information on the institutional setting of US pharmaceuticals. Section 3 provides information on our data, sample construction, and descriptive statistics. Section 4 outlines our empirical design comparing firms with completed and withdrawn IPOs. Section 5 presents results on how IPOs affect innovation outcomes, and Section 6 shows the impact to hiring patterns. Section 7 concludes.

## 2 Setting: Pharmaceuticals

The US pharmaceutical industry, one of the largest sectors in terms of domestic R&D spending, provides a useful and important setting to examine how public financing influences product development outcomes. In particular, the pharmaceutical sector makes up roughly 17 percent of total industrial R&D and 62 percent of industrial R&D in health care (National Science Foundation and Census Bureau, 2018). Using comprehensive data on project-level investments for pharmaceutical firms, we are able to accurately document how public finance shapes firms' innovation decisions throughout the R&D process.

In the US, drug development consists of a series of phases: The process typically begins with extensive preclinical laboratory research that involves testing a new drug candidate in animals and human cells. Once complete, drug manufacturers begin the most expensive aspect of drug development: human testing of drugs in a series of clinical trials with costs that increase with each subsequent phase. Drugs that successfully demonstrate safety in Phase I trials proceed to Phase II trials in which their efficacy is tested in a few hundred patients. Phase III is the final stage of pre-market clinical development and involves assessing efficacy in thousands of patients and examining them over a longer period of time. Upon successfully completing the Phase III trials, the sponsor will submit a New Drug Application (NDA) or Biologics License Application (BLA) to the US Food and Drug Administration (FDA) for approval. Once approved, firms may choose to conduct additional safety clinical trials or to seek FDA approval for additional therapeutic uses.

The entire process is long (often lasting between 8 to 12 years), costly (typically costing a manufacturer $300 million to $2.6 billion for the development of a brand new molecule), and risky (only 9 percent of drugs that enter clinical trials ultimately reach the market) (Adams and Brantner, 2006; CSDD, 2014; Danzon and Keuffel, 2014; DiMasi, 2001; DiMasi et al., 2003; Wouters et al., 2020). For these reasons, the financial capital infusion that comes via an IPO is especially important.

## 3 Data and Descriptive Statistics

### 3.1 Drug Development Data

Our drug development information comes from two databases: the Cortellis Competitive Intelligence and Cortellis Competitive Clinical Trials Intelligence databases. The Cortellis Competitive Intelligence database is a comprehensive dataset covering drug development activity for more than 240,000 firms. The database provides detailed information about all drugs in a firm's research portfolio and documents each drug's progression from preclinical development to launch and discontinuation. For each drug, we are able to observe its development stage (e.g., Phase III), start of the development stage (e.g., January 15, 2005), and disease under investigation (e.g., colorectal cancer). We supplement this information using detailed clinical trial data from Cortellis Competitive Clinical Trials Intelligence, which includes over 500,000 global and US-based clinical trials from 24 clinical trial registries around the world. Using this dataset, we incorporate detailed clinical trial characteristics, such as the trial sponsor (e.g., Genentech), trial design (e.g., randomized, double-blind, controlled), and any reported clinical outcomes (e.g., share of patients whose tumors respond to treatment).

To assess how public financing shapes subsequent research activity, we determine the total level of research projects associated with a given firm in a given year. In particular, we examine the number of research projects in seven development stages: pre-clinical research, Phase I, Phase II, Phase III, and regulatory approval. We supplement the outcomes on research projects by also measuring

innovative activity via a firm's patents. Next, we go beyond these raw counts by investigating how public financing shapes the composition and quality of subsequent product development. To understand changes in research composition, we look at the extent to which the research projects involve a therapeutic area that the firm has or has not previously investigated.

### 3.2 Employment Data

To understand how public markets alter firms' hiring patterns, and the extent to which these hiring decisions influence innovation outcomes, we turn to workforce data from Revelio Labs. Revelio Labs collects and standardizes all publicly available employment records, such as from online profiles like LinkedIn, job postings, and employee sentiment reviews. The data cover more than 24 million companies and 1.1 billion individuals worldwide. With this dataset, we gain the professional history of individuals—including their employers, job titles, and start and end dates of each position. From the Revelio data, we can ascertain the date each employee joins one of our sample firms, the experience of employees at those firms, and their job categories. Note that as the Revelio data rely on self-reporting through LinkedIn, we make use of Revelio-provided weights to have a fully representative sample of employees at each company.

We begin our analyses into hiring patterns by determining the total number of employees, in general and across different job categories, in each year for each firm in our analytic sample. Next, we explore how public financing alters hiring flows by looking at new hiring versus incumbent retention rates, and we examine the prior experience of any new hires.

### 3.3 IPO Data

We collect IPO data from Standard & Poor's (S&P) Capital IQ, Moody's Zephyr, and the SDC New Issues database. We determine, for each firm's IPO, the initial filing date, the offer date, the associated exchange, and, if relevant, the withdrawal date. We address any discrepancies in these dates across the three datasets via manual review. We restrict to US exchanges and incorporate IPO information into our firm-year dataset (described below) through both ID-based matching (e.g., using firms' CIK and ISIN keys, when available) and fuzzy matching algorithms.

### 3.4 Firm Sample

To build our analytic dataset, we begin with the sample of research-intensive pharmaceutical and biotechnology firms in the Cortellis data, meaning that we observe the firm as the sponsor for at least one clinical trial in the data. We then use a multistep cleaning process to create an unbalanced firm-year panel. First, since related firm entities can have slightly different names in the database, we follow algorithmic and manual approaches to clean and group firm names together. We then link firms to both the Revelio and IPO data using exact and fuzzy matching algorithims. We restrict

our sample to the set of firms with initial IPO filing years between 2000 and 2019 and that have at least one clinical trial prior to the IPO filing. More information on the construction of the final "stacked" dataset is provided in Section 4, which outlines our empirical strategy.

### 3.5 Descriptive Statistics

Table 1 provides firm-year level summary statistics for firms that either completed or withdrew their IPOs, focusing on the period prior to the IPO filing. We find that on average, firms with completed IPOs invested in 2.1 preclinical development projects and initiated 4.3 clinical trials each year. Across various measures of innovative activity—rate, direction, and quality—we find little difference between firms with completed and withdrawn IPOs. The few exceptions are for trials with novel mechanisms of action, total number of patents, and number of product patents, where we find that firms completing their IPOs have higher values relative to those that file and withdraw. Taken together, this descriptive evidence suggests that firms with withdrawn IPOs can serve as a suitable control group for firms with a completed IPO.

## 4 Empirical Design

A main challenge in estimating the causal effect of an IPO on a firm's subsequent innovation and hiring decisions is creating an appropriate counterfactual for the firm's activities had it not gone public. Because firms endogeneously select into the decision to go public, we cannot simply compare private and public firms. Rather, we follow Bernstein (2015) and look at the set of private firms that file for an IPO with the SEC; those firms that then withdraw the filing and remain private serve as controls for those that complete the IPO and go public.

For each filing year from 2000 through 2019, we construct a cohort of treated firms (that complete the IPO) and control firms (that withdraw the IPO) with that filing year. We restrict to windows five years before and after the IPO filing, "stacking" the data for each cohort. The resulting dataset has 3,432 firm-year-cohort observations. With this dataset, we estimate "stacked" difference-in-differences regressions (Cengiz et al., 2019; Gormley and Matsa, 2011) for firm $i$ of IPO filing year cohort $c$ in the years $t \in \{-5, 5\}$ surrounding the filing at $t = 0$:

$$Y_{ict} = \beta Post_t \times IPO_{ic} + \delta_{ic} + \delta_{tc} + \varepsilon_{ict} \tag{1}$$

Here, $Y$ is the relevant innovation or employment outcome; $Post$ specifies the period following an IPO filing; $IPO$ is an indicator for whether firm $i$ in cohort $c$ is treated or not; $\delta_{ic}$ are firm-cohort fixed effects; and $\delta_{tc}$ are cohort-year fixed effects. The coefficient of interest is $\beta$, providing the average treatment effect of going public on a firm's innovation or hiring decisions. We do not include time-varying firm characteristics in the regression as these could themselves be affected by the IPO

event and would prevent a consistent estimate of $\beta$ (Gormley and Matsa, 2011). For instance, any changes to R&D expenditures following an IPO event are likely due to the IPO event and thus part of the treatment effect we wish to capture. If we included R&D expenditures as a control in the regression, $\beta$ would then only measure the portion of the IPO effect that is uncorrelated with the causal impact of the IPO on R&D expenses. We use robust standard errors clustered at the firm level.

## 5 Results: Effect of IPOs on Innovation

### 5.1 Innovation Levels

We begin by exploring how the transition to public markets influences the level of innovation activity, first with respect to project development and then with respect to patenting. Table 2 reports the effect of going public on innovation levels across different stages of the drug development process. Columns (1)–(5), respectively, ask whether going public leads to an impact on the likelihood that a firm initiates investment in preclinical research, a phase I trial, a phase II trial, a phase III trial, any trial (regardless of phase), and any drug approval. Across the preclinical and all clinical trial stages, we observe a positive and statistically significant impact of going public on the level of subsequent innovative activity. At the mean of the dependent variable, the estimated coefficient of 0.239 in Column (1) suggests a 50-percent increase in the likelihood of a preclinical research investment following a firm's initial public offering. This increase also extends to clinical research: The estimated coefficient of 0.253 in Column (5) indicates that an IPO increases the likelihood that a firm initiates clinical research investment by 46 percent. Notably, in Column (6), we find no effect on the probability of drug approvals. This is not surprising given we restrict to windows of five years surrounding the IPO filing, and as discussed in Section 2, the drug development process for approved drugs lasts from 8 to 12 years on average.

In Table 3, we examine the impact of IPOs on pharmaceutical firms' patenting activities. Again, we find an increase in the total level of innovation. In Column (1), we see that going public raises the likelihood of obtaining any patent by 14 percentage points, for a 24-percent increase relative to firms that withdraw their IPOs. However, restricting to product patents in Column (2), we observe no effect. These results are in line with the results above in Table 2, where we find significant increases in trial activity, meaning firms that complete an IPO increase efforts to develop new drugs in the five years post-IPO, but experience no change as of yet in commercialization, as going fully through the drug development and approval process takes several years.

Figure 1 provides event studies examining the time trends of these innovation levels surrounding an IPO filing. Specifically, we plot the treatment effect over time for firms that complete their IPOs relative to those that withdraw their filings. Panel (a) looks at any clinical trial activity while

Panel (b) depicts any patenting activity. The parallel trends assumption for difference-in-differences analyses requires that trends in innovation outcomes for firms that go public would be the same as those that file and withdraw, in absence of the completed IPO. While there is some noise, our event study plots provide evidence supporting the parallel trends assumption that there does not appear to be any difference in trends before IPO filing of firms that complete their IPOs versus those that withdraw them. We show a sustained increase in both the probability of conducting any trial and obtaining any patent for firms that go public over the five years following their IPO filings.

### 5.2 Innovation Quality and Novelty

Table 4 probes the effect of going public on the quality and novelty of subsequent R&D activity. The design of a clinical trial plays an important role in shaping the quality of the information generated, with better-designed trials often providing more reliable evidence of a drug's safety and efficacy. For example, patient randomization, in which participants are assigned to treatment and control arms, helps minimize patient selection biases. Columns (1)–(3) of Table 4 show that an IPO increases firm investment in high-quality trials, namely those that are randomized, blinded, or controlled. Column (4) examines whether an IPO changes the likelihood that a firm conducts a trial on drugs of greater novelty. However, we observe no effect on the likelihood that firms clinically test drugs with novel mechanisms of action.

### 5.3 Innovation Direction

In Table 5, we examine how firms shift the direction of their innovative activity following their IPOs. To do this, we categorize firms' clinical trial activity into two groups: (1) trials targeting diseases already tested by drugs in the firm's R&D pipeline and (2) trials targeting diseases not already tested by drugs in the R&D pipeline. We use Medical Subject Heading (MeSH) codes, a hierarchical controlled vocabulary maintained by the National Library of Medicine, to categorize diseases. We consider two levels of disease similarity: trials within the same 3-digit MeSH code (representing broader disease categories, such as respiratory tract diseases or eye diseases) and trials within the same 6-digit MeSH code (for more narrow disease conditions, such as lung diseases or eye infections). Columns (1) and (2) of Table 5 show that the post-IPO increase in research activity documented in Table 2 is largely driven by investment in diseases that firms have previously researched. In contrast, Columns (3) and (4) indicate that firms are unlikely to expand their R&D efforts to include diseases they have not explored before. Taken together, these findings indicate that following an IPO, firms increase their research in familiar domains rather than exploring new ones. These results are also consistent with our findings above where we observe no effect on the likelihood that firms clinically test drugs with novel mechanisms of action.

## 6 Results: Effect of IPOs on Hiring Patterns

### 6.1 Employment Levels

Table 6 examines the impact of going public on employment levels. Column (1) looks at total employment. The 0.446 coefficient indicates that firms that complete their IPOs increase their labor forces by 56 percent ($100 \times (e^{0.446} - 1) = 56.2$) relative to those that remain private, and relative to their own baselines. As the Revelio data provide information on job titles, we next use machine learning methods to classify all job titles in our analytic file to broader job categories. For instance, "Clinical Researcher" and "Development Scientist" are classified as "scientific" positions while "Quality Assurance Expert" and "Regulatory Affairs Analyst" are classified as "regulatory" positions. In Columns (2) through (5), we see similar numbers to the total employment figure across four main employee categories—regulatory, scientific, commercial, and operations—with all coefficients significant at the 1-percent level. These results suggest that IPOs provide a cash infusion and potential publicity allowing firms to substantially grow their labor forces.

### 6.2 Hiring Flows

In Table 7, we move beyond aggregate employee volumes to begin exploring hiring flows. Column (1) repeats the specification from Table 6 showing the effect of going public on total employment. Column (2) evaluates retention of incumbents. The 0.490 coefficient gives the within-firm differential change in incumbent retention for firms that complete their IPOs relative to those that withdraw; it suggests that firms moving to public ownership retain 63 percent ($100 \times (e^{0.490} - 1) = 63.2$) more incumbents. Column (3) shows that they also hire 41 percent ($100 \times (e^{0.346} - 1) = 41.3$) more new employees per year.

Figure 2 provides the event study plot showing trends in new hires surrounding the IPO filing for firms that go public versus those that file and withdraw. While there is some noise in the estimates, we again are reassured of the parallel trends assumption that there does not appear to be systematic differences between these two groups of firms prior to the IPO filing. We see that firms transitioning to public equity markets immediately raise their hiring in the first year following the IPO announcement and have slightly lower, but sustained, rates of increased hiring over years 2 through 4. Hiring rates return to the firms' baselines by year 5.

### 6.3 New Hire Experience

Table 8 explores the composition of new hires in terms of experience. Using the Revelio data, we are able to track employees' job histories and develop measures of experience at the time they are hired by one of our sample firms, relative to their first year of employment anywhere. Column (1) repeats the specification from Table 7 where the amount of new hires is the dependent variable.

Columns (2) through (5) subset the number of new hires based on years of experience. In Column (2), we see that firms transitioning to public ownership do not increase their rate of hiring of less experienced employees (with between 0 and 4 years of prior experience). Rather, they concentrate their hiring growth among more experienced employees. In particular, firms that go public hire 34 percent ($100 \times (e^{0.294} - 1) = 34.2$) more employees with between 10 and 19 years experience relative to firms that stay private, and relative to their own baselines.

## 7 Conclusion

This paper studies how the transition from private to public ownership shapes innovation outcomes and hiring flows in the US biopharmaceutical industry. Our research design compares firms that complete an IPO with firms that file and withdraw, and we use detailed data on drug development portfolios, clinical trial design, patents, and person-level employment histories. We show that going public has economically and statistically meaningful effects on both R&D activity and workforce composition. Post-IPO firms are more likely to initiate clinical trial research activity and those clinical trials are of higher quality. At the same time, the additional R&D is concentrated in diseases already represented in firms' pipelines.

We also find that IPOs are followed by large increases in employment overall and across scientific, regulatory, commercial, and operations job categories. Further, firms that go public experience higher incumbent retention and new employee hiring. The hiring response is strongest among workers with greater prior experience. These patterns suggest that going public relaxes important resource constraints not only by providing financial capital, but also by improving firms' ability to attract and retain human capital. At the same time, the concentration of post-IPO R&D in previously explored disease areas is consistent with public ownership increasing the salience of external scrutiny, short-termism, and risk mitigation. Overall, our findings point to a nuanced view of how public markets affect innovation outcomes. More generally, the results highlight the value of moving beyond patents when measuring innovation and of considering labor market responses as a central channel through which financing shapes firm behavior.

## 8 Tables and Figures

Table 1: Summary Statistics. Completed vs. Withdrawn IPOs Before IPO

| | Completed | | Withdrawn | | |
|---|---|---|---|---|---|
| | Mean (1) | SD (2) | Mean (3) | SD (4) | $p$-value (5) |
| **Project Investment Levels** | | | | | |
| Preclinical Activity | 2.05 | 4.64 | 1.83 | 2.88 | .52 |
| Phase 1 Trials | 1.03 | 4.23 | .46 | .78 | .13 |
| Phase 2 Trials | 1.86 | 10.73 | .84 | .81 | .29 |
| Phase 3 Trials | .91 | 6.08 | .36 | 1.07 | .31 |
| All Trials | 4.3 | 25.55 | 1.67 | 1.3 | .25 |
| Drug Approvals | 1.1 | 11.85 | .07 | .3 | .22 |
| **Project Selection** | | | | | |
| Trial in Previously Tested 3-Digit MeSH | 4.87 | 30.08 | 1.13 | 1.45 | .23 |
| Trial in Previously Tested 6-Digit MeSH | 4.85 | 30.02 | 1.11 | 1.45 | .23 |
| Trial in Novel 3-Digit MeSH | .63 | .48 | .63 | .48 | .88 |
| Trial in Novel 6-Digit MeSH | .65 | .48 | .66 | .48 | .91 |
| **Project Quality and Novelty** | | | | | |
| Randomized | 2.42 | 13.1 | 1.01 | 1.12 | .23 |
| Multi-blinding | 1.72 | 8.26 | .91 | 1.14 | .27 |
| Controlled | 2.09 | 10.68 | 1.02 | 1.2 | .26 |
| Novel Mechanism of Action | .14 | .53 | .04 | .2 | .03 |
| **Patenting** | | | | | |
| All Patents | 3.05 | 12.72 | 1.53 | 2.09 | .04 |
| Product Patents | 2.2 | 7.48 | .72 | 1.14 | .01 |

Notes: This table shows research characteristics for firms with completed and withdrawn IPOs before the completed/withdrawn IPO. All variables are measured at the firm-year-level. Column (5) presents $p$-values from $t$-tests comparing the difference of means.

Table 2: Effect of an IPO on Project Investment Levels

| | Any Preclinical Activity (1) | Any Phase I Trial (2) | Any Phase II Trial (3) | Any Phase III Trial (4) | Any Trial (5) | Any Drug Approval (6) |
|---|---|---|---|---|---|---|
| *Post*×*IPO* | 0.239*** | 0.100*** | 0.207*** | 0.102*** | 0.253*** | 0.0285 |
| | (0.0518) | (0.0374) | (0.0442) | (0.0388) | (0.0480) | (0.0298) |
| Mean of Dep. Var. | 0.478 | 0.254 | 0.340 | 0.185 | 0.552 | 0.115 |
| Observations | 3,432 | 3,432 | 3,432 | 3,432 | 3,432 | 3,432 |
| Cohort-Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table reports stacked DiD estimates of the effect of going public on the level of innovative activity, across different stages of the drug development process. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in each column is an indicator for research activity in each stage of the drug development process. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-firm fixed effects and cohort-year fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

Table 3: Effect of an IPO on Patenting Activity

| | Any Patent (1) | Any Product Patent (2) |
|---|---|---|
| *Post*×*IPO* | 0.119** | 0.0285 |
| | (0.0517) | (0.0420) |
| Mean of Dep. Var. | 0.590 | 0.294 |
| Observations | 3,432 | 3,432 |
| Cohort-Firm FE | Yes | Yes |
| Cohort-Year FE | Yes | Yes |

Notes: This table reports stacked DiD estimates of the effect of going public on patenting. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in Column (1) is an indicator for any patent and the dependent variable in Column (2) is an indicator for any product patent. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-firm fixed effects and cohort-year fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

TABLE 4: EFFECT OF AN IPO ON PROJECT QUALITY AND NOVELTY

| | Any Randomized Trial (1) | Any Blinded Trial (2) | Any Controlled Trial (3) | Any Trial with Novel MOA (4) |
|---|---|---|---|---|
| *Post*×*IPO* | 0.179*** | 0.177*** | 0.192*** | -0.0112 |
| | (0.0421) | (0.0373) | (0.0440) | (0.0139) |
| Mean of Dep. Var. | 0.408 | 0.344 | 0.395 | 0.041 |
| Observations | 3,432 | 3,432 | 3,432 | 3,432 |
| Cohort-Firm FE | Yes | Yes | Yes | Yes |
| Cohort-Year FE | Yes | Yes | Yes | Yes |

NOTES: This table reports stacked DiD estimates of the effect of going public on the quality and novelty of innovative activity. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in each column is an indicator for measures of either quality or novelty in clinical trial activity. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-firm fixed effects and cohort-year fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

TABLE 5: EFFECT OF AN IPO ON PROJECT SELECTION

| | Any Trial in Disease Previously in Firm's R&D Pipeline | | Any Trial in Disease Novel to Firm's R&D Pipeline | |
|---|---|---|---|---|
| | Same 3-Digit MeSH | Same 6-Digit MeSH | Different 3-Digit MeSH | Different 6-Digit MeSH |
| | (1) | (2) | (3) | (4) |
| *Post*×*IPO* | 0.158*** | 0.157*** | 0.0563 | 0.0561 |
| | (0.0340) | (0.0341) | (0.0367) | (0.0367) |
| Mean of Dep. Var. | 0.470 | 0.466 | 0.252 | 0.263 |
| Observations | 2,357 | 2,357 | 2,357 | 2,357 |
| Cohort-Firm FE | Yes | Yes | Yes | Yes |
| Cohort-Year FE | Yes | Yes | Yes | Yes |

NOTES: This table reports stacked DiD estimates of the effect of going public on the direction of innovative activity. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in each column is an indicator for research activity in either the same or different MeSH codes as a firm's existing R&D pipeline. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-firm fixed effects and cohort-year fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

Table 6: Effect of an IPO on Employment Levels

| | ln(Total Employees) (1) | ln(Regulatory Employees) (2) | ln(Scientific Employees) (3) | ln(Commercial Employees) (4) | ln(Operations Employees) (5) |
|---|---|---|---|---|---|
| *Post*×*IPO* | 0.446*** | 0.422*** | 0.488*** | 0.436*** | 0.455*** |
| | (0.138) | (0.145) | (0.144) | (0.136) | (0.137) |
| Mean of Dep. Var. | 3.745 | 1.468 | 2.734 | 2.014 | 2.500 |
| Observations | 2,294 | 2,294 | 2,294 | 2,294 | 2,294 |
| Cohort-Firm FE | Yes | Yes | Yes | Yes | Yes |
| Cohort-Year FE | Yes | Yes | Yes | Yes | Yes |

Notes: This table reports stacked DiD estimates of the effect of going public on employment levels. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in each column is the natural log of the number of employees. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-firm fixed effects and cohort-year fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

Table 7: Effect of an IPO on Hiring Flows

| | ln(Total Employees) (1) | ln(Incumbents) (2) | ln(New Hires) (3) |
|---|---|---|---|
| *Post*×*IPO* | 0.446*** | 0.490*** | 0.346** |
| | (0.138) | (0.135) | (0.164) |
| Mean of Dep. Var. | 3.745 | 3.496 | 2.204 |
| Observations | 2,294 | 2,294 | 2,294 |
| Cohort-Firm FE | Yes | Yes | Yes |
| Cohort-Year FE | Yes | Yes | Yes |

Notes: This table reports stacked DiD estimates of the effect of going public on incumbent retention and hiring flows. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in each column is the natural log of the number of employees. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-year fixed effects and cohort-firm fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

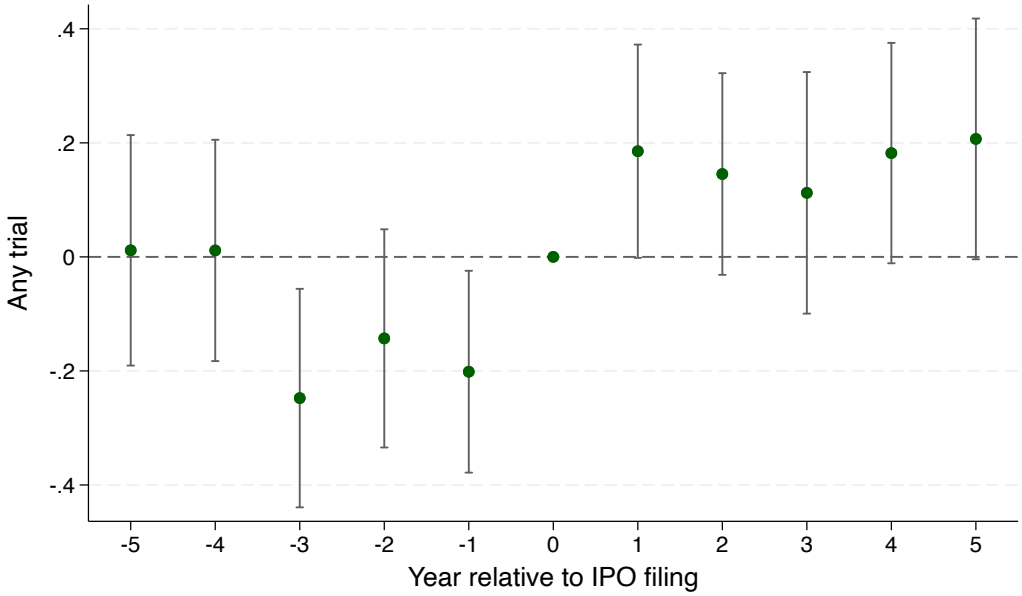
Table 8: Effect of an IPO on New Hire Experience

| | ln(New Hires) (1) | ln(New Hires: 0-4 Years Experience) (2) | ln(New Hires: 5-9 Years Experience) (3) | ln(New Hires: 10-19 Years Experience) (4) | ln(New Hires: $\geq$ 20 Years Experience) (5) |
|---|---|---|---|---|---|
| *Post*×*IPO* | 0.346** | 0.0987 | 0.201* | 0.294** | 0.125** |
| | (0.164) | (0.0950) | (0.103) | (0.139) | (0.0553) |
| Mean of Dep. Var. | 2.204 | 0.614 | 1.111 | 1.334 | 0.272 |
| Observations | 2,294 | 2,294 | 2,294 | 2,294 | 2,294 |
| Cohort-Firm FE | Yes | Yes | Yes | Yes | Yes |
| Cohort-Year FE | Yes | Yes | Yes | Yes | Yes |

Notes: This table reports stacked DiD estimates of the effect of going public on new hire experience. Observations are at the cohort-firm-year level. Estimates are from OLS models. The dependent variable in each column is the natural log of the number of employees. *Post*×*IPO* switches from 0 to 1 when a firm completes an IPO. All columns include cohort-firm fixed effects and cohort-year fixed effects. Robust standard errors, clustered at the firm level, are shown in parentheses. *$p$ <0.10; **$p$ <0.05; ***$p$ <0.01.

FIGURE 1: EVENT STUDIES EXAMINING INNOVATION ACTIVITY

**(a)** Firm conducts any trial




**(b)** Firm files any patent

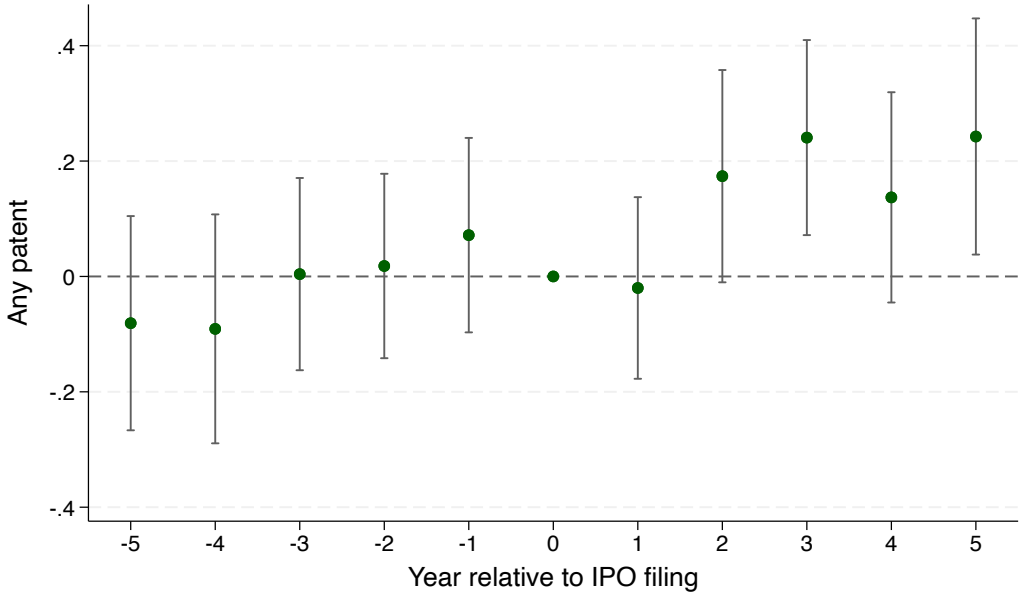
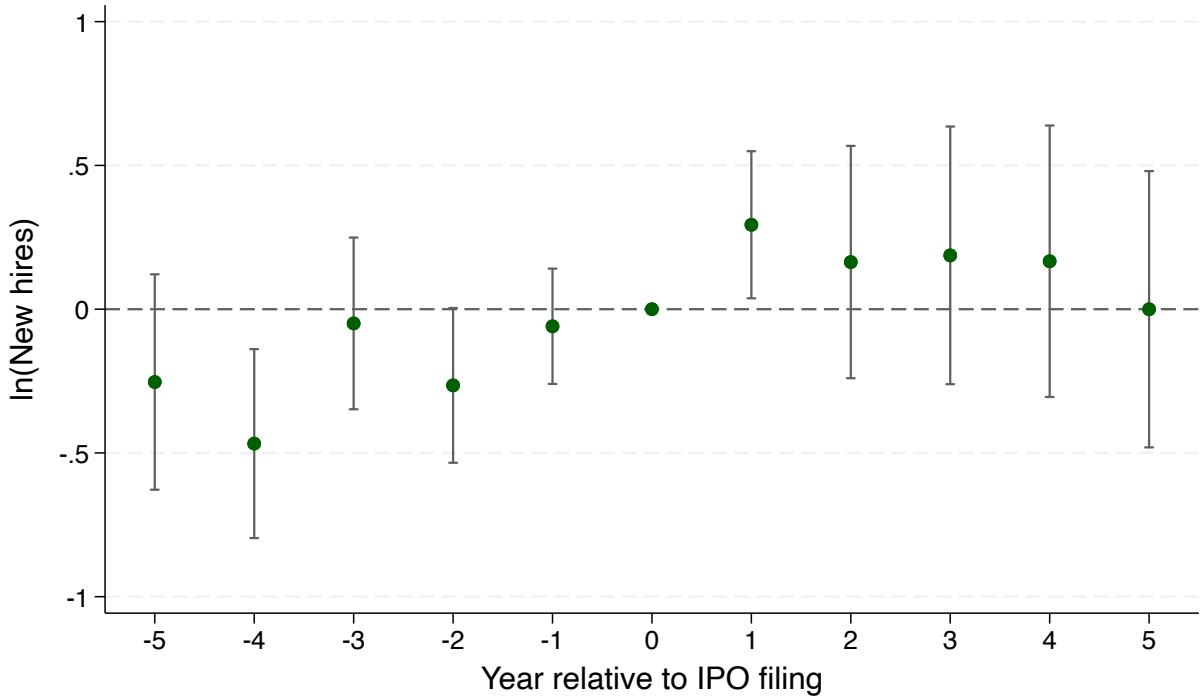


FIGURE 2: EVENT STUDY EXAMINING HIRING FLOWS



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