IPO Peer Effects*

Cyrus Aghamolla† Richard T. Thakor‡

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Abstract

This study investigates whether a private firm's decision to go public affects the IPO decisions of its competitors. Using detailed data from the drug development industry, we identify a private firm's direct competitors at a precise level through a novel approach using similarity in drug development projects based on disease targets. The analysis shows that a private firm is significantly more likely to go public after observing the recent IPO of a direct competitor, and this effect is distinct from "hot" market effects or other common shocks. Furthermore, our effects are centered on firms that operate in more competitive areas. We additionally explore peer effects in private firm funding propensities more broadly, such as through venture capital or being acquired, and find results consistent with a competitive channel.

Keywords: Initial public offerings, IPO propensity, peer effects, R&D competition, information spillovers.
JEL classification: D22, G14, G32, O31.

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†University of Minnesota. E-mail: caghamol@umn.edu.
‡University of Minnesota and MIT LFE. E-mail: rthakor@umn.edu.

1 Introduction

How are the initial public offering (IPO) plans of a private firm related to that of a close rival? This question is relevant for the fundamental issue of the determinants of private and public ownership in the economy (see, e.g., Stulz, 2019 for a documentation of recent trends). In frictionless financial markets, a firm's IPO decision should not be influenced by their competitors' decisions. However, anecdotally, we observe close industry competitors often framing their IPO decisions as a response to the actions of their rivals. For example, in the nascent share-economy industry, Uber is reported to have sped up its IPO plans after getting wind that Lyft would soon tap public markets. Relatedly, in the cyber-security industry, Tenable is reported to have sped up its IPO plans by several quarters after observing the IPO of one of its close competitors, Zscaler.[1]

A natural question that arises is whether competing firms respond to a *direct* competitor's decision to transition to public equity markets. In general, firms must weigh the costs and benefits when deciding whether to go public or to remain private. Observing the IPO of a close rival may affect this tradeoff due to competitive or informational incentives. For example, going public can confer competitive advantages to the newly public firm, such as attracting investor and consumer attention, providing capital to expand or advance project development and facilitate acquisitions, and enhanced compensation options for hiring talented agents. Consequently, private peers may be compelled to go public following a competitor in order to mitigate this competitive edge (i.e., the benefit of remaining private decreases). A competitor's IPO can also carry informational spillovers to still-private peer firms, such as how the offering was received by investors, both in terms of underpricing and proceeds, or on the viability of a new project or technology. Moreover, the underwriter's costly information acquisition regarding the valuation of the competitor firm may be revealed during the marketing and bookbuilding process of the competitor's IPO (e.g., Benveniste, Ljungqvist, Wilhelm, and Yu, 2003). This allows private peer firms to freeride on the information produced, resulting in a lower marginal cost to going public.

In this paper, we seek to investigate whether a firm's IPO propensity is affected by the IPO decisions of its *direct* competitors, which we refer to as "peer" firms. A major challenge in this exercise is that it requires data on private firms—both those that go public and those that remain private—as well as the ability to identify close rivals among these firms. This is generally difficult due to the limited information on U.S. private companies, as their financial

[1]See "What Lyft's IPO Means for Uber, Pinterest and Other Tech Unicorns," *The Street*, March 31, 2019.

statements and operating decisions are not publicly available.[2] We attempt to overcome this obstacle by considering private firms within a specific industry—the biopharmaceutical (biopharma) industry—for which we have detailed project-level data. This approach allows us to identify and construct a precise measure of each firm's direct competitors, based on the commonality of individual projects (i.e., the specific diseases being targeted by drugs) in development, and to observe their history of staying private or going public. By focusing on a single industry and exploiting project-level heterogeneity between firms, we are able to identify peer effects in the propensity of going public at the firm-level that are distinct from more general phenomena related to "hot" markets, IPO waves, or other types of common shocks that have been previously documented (e.g., Ibbotson and Jaffe, 1975).

We specifically define a peer firm as a firm pursuing a project in the same therapeutic indication category (e.g., "Rheumatoid Arthritis") as another firm. This is a granular distinction as there are 669 therapeutic categories specific to particular diseases, with the majority of firms developing drugs in two or fewer therapeutic areas. There are a number of advantages to this approach. First, we are able to identify peers in a natural way that depends on the precise projects undertaken by the firm. This allows for a more specific and fine-tuned measure of peer firms whose actions the focal firm are likely to follow closely, in contrast to the often-used definition of peer groups at the industry level.[3] Second, this classification of peers is *firm-specific*. Each firm's peer group is based on firm-specific characteristics (project portfolios), and leads to the presence of *partially overlapping* peer groups across firms. As we discuss in more detail later, because peer groups can differ for each firm based on their project portfolios, our empirical strategy solves the reflection problem (i.e., simultaneity), which refers to the inability to disentangle the different effects that can influence peer behavior (Manski, 1993). While this is typically a major identification challenge in estimating peer effects, our peer group specification allows us to distinguish the effect of a peer IPO from other peer covariates that may influence the focal firm's IPO decision. Moreover, the presence of partially overlapping peers permits an instrumental variables (IV)

[2]As a consequence, the extant literature has largely considered IPO and competition effects at the industry level, and has generally examined the effects on public firms (e.g., Hsu, Reed, and Rocholl, 2010).

[3]A similar approach is developed in the innovative work of Hoberg and Phillips (2016), who determine a firm's product market competitors through the similarity in product descriptions in 10-K filings. The advantage of our measure is that we have project information for both public and private firms, whereas Hoberg and Phillips (2016) generally applies only to public firms due to the lack of 10-K filings from private firms. Additionally, we are able to directly observe the exact project categories that firms are working in, which allows a more precise classification of a firm's competitors than through textual analysis. Finally, we are able to observe the projects a firm has *in development*, which allows us to identify both R&D competitors and product market competitors, whereas the measure of Hoberg and Phillips (2016) primarily focuses on product market competitors.

approach that helps to alleviate concerns related to unobserved common shocks. Third, our approach allows us to track a firm's competitors over time in line with changes in their project portfolios. Finally, we are able to examine the interactions of *private* firms, which has been relatively unexplored in the peer effects literature.

We find that private firms are significantly more likely to transition to public equity markets when a close competitor has recently gone public. We find that observing a peer firm go public within the previous 12 months increases the probability of going public by 40 percent, from an unconditional baseline propensity to go public of 0.31 percent per quarter to 0.44 percent per quarter. Moreover, this increase in the propensity to go public represents an increase of 62 percent compared to the IPO propensity of firms that do not observe a peer IPO (a change from 0.20 percent per quarter to 0.33 percent per quarter). When run at a yearly frequency, our estimates imply an increase from an unconditional baseline propensity to go public of 1.22 percent per year to 2.04 percent per year. This result holds after controlling for time and firm fixed effects, market conditions, the number of IPOs, and the risk and size of the project portfolio, and also remains when accounting for other common shocks between firms.

We then further investigate the channels by which this effect arises. As discussed above, going public may give firms a competitive edge—in order to stay competitive, rival firms may initiate or accelerate their IPO plans and quickly go public following their peer. Consistent with this argument, we find that the increase in IPO propensity is concentrated among firms in more competitive therapeutic indication areas. Likewise, firms can benefit from informational externalities when their rivals go public, which may lead to lower IPO costs for these firms. In particular, firms must engage in costly information acquisition regarding their valuation when pricing the offering (Hanley and Hoberg, 2010). Hence, observing the IPO and corresponding disclosures (such as the IPO prospectus) of a direct competitor working in the same project area may allow still-private peers to freeride off of the evaluative information produced, thus lowering the IPO costs for a private peer (Benveniste, Busaba, and Wilhelm Jr, 2002). To explore this channel, we examine the IPO outcomes for firms that follow a close competitor's IPO decision relative to the competitor's IPO outcomes. These outcomes are those that we expect to be affected when firms have enhanced information, such as the amount of time between filing and IPO completion, the level of underpricing, or proceeds raised from the IPO. In contrast to the informational hypothesis, we do not find any significantly distinguishable effects in these outcomes for follower firms versus non-followers. Collectively, these results suggest that the increase in IPO propensity following rival firm

IPOs is driven by competitive pressures.

To further explore the mechanism driving our main result, we distinguish our direct competitor measure by whether the rival firms are R&D competitors or product market competitors. Specifically, firms that have drugs in development in the same therapeutic category are R&D competitors, while a firm that has an approved (e.g., marketed) drug in the same category is a product market competitor. We find that an IPO by an R&D competitor increases the focal firm's propensity of going public, while an IPO by a product market competitor has an insignificant effect on IPO propensity. This is consistent with theories of competition in innovation, such as Aghion, Bloom, Blundell, Griffith, and Howitt (2005), which predict that firm responses to competitive pressures depend on the extant nature of competition they face.[4]

A concern in any setting that explores peer effects is that the results are driven by unobservable common shocks between firms (unrelated to peer effects) or other endogeneity/reverse causality concerns. For example, the decision of a peer firm to go public is endogenous, and one way this decision could manifest itself is through a correlation across time in firm going-public decisions. We further establish that such concerns do not drive our results through a number of additional tests. First, we saturate our main specification with a wide variety of additional fixed effects that control for common shocks across firms that operate in given disease groups. These time-varying fixed effects specifically control for common shocks impacting firms within broader disease groups *by period*. Hence, this procedure accounts for any correlated information arrival or common shock that influences the IPO decisions of similar firms within each period. Our results remain even when controlling for these effects. These tests also provide evidence that our granular measure of peer effects retains explanatory power even when explicitly accounting for effects that operate across broader peer groups.

Second, we account for broader endogeneity and reverse causality concerns by running an instrumental variable (IV) specification where we exploit the structure of peer groups in our setting, and the fact that the peer groups only partially overlap (e.g., De Giorgi, Pellizzari,

[4]Aghion et al. (2005) predict that increasing competition will discourage laggard firms (firms that face a large gap between themselves and leaders) from innovating, while it will encourage firms that face neck-and-neck competition to innovate further. In particular, our finding that a firm responds to an R&D rival that goes public suggests that the focal firm seeks to continue to compete in neck-and-neck competition by going public themselves. However, the competitive advantage from going public that is conferred to a rival who already has an approved drug may prove to be too large a gap for the focal firm to overcome, resulting in an unchanged IPO propensity. These firms staying private to potentially explore other areas is consistent with models that predict that such activities are optimally done in private firms (Ferreira, Manso, and Silva, 2014; Boot and Vladimirov, 2018).

and Redaelli, 2010). In particular, we instrument for the probability that a focal firm's peer does an IPO by utilizing the IPO decision of a competitor of the peer firm (but that is *not* a direct competitor to the focal firm).[5] Through the IV specification, we again find strongly consistent results. We additionally consider a specification where instruments exclude peers of peers that operate within the same ICD-10 block—a much broader grouping of disease groups—as the focal firm, to further alleviate potential concerns of underlying similarity. Our results remain strongly consistent even under this more restrictive definition of peers of peers.

In our final analyses, we explore whether peer effects operate more broadly across other funding opportunities available to private firms, in addition to IPOs. More specifically, as an alternative to going public, private firms are able to obtain funding through venture capital (VC) or by being acquired by a larger firm. The channels at work with our IPO peer effects may operate through these other funding channels. We find evidence of peer effects with VC funding, being acquired, and also more general funding peer effects combining these two channels and IPOs. However, when examining these peer effects more closely, we find that the *scale* of the funding source by the competitor plays a role in the firm's response. In particular, VC funding peer effects are present only with relatively large VC funding rounds, and firms do not turn to VC funding when their peers are acquired or go public. In contrast, going public and being acquired are both significant responses to observing a peer obtain any type of funding, with the strongest effects centering on firms choosing to go public as a response.

These results are consistent with the aforementioned competitive channel—in order to remain competitive with their rivals, firms raise capital after observing the increased capital of a close competitor. Moreover, this effect is salient for funding that provides large capital increases by competitors, and firms respond with sources that allow funding increases of their own. The results also provide evidence that firms are relatively more inclined to choose going public over selling the firm or raising VC funding in response to a peer's funding decision. This suggests that IPO funding is particularly important in terms of peer effects due to the magnitude of funding involved, which allows firms to maintain competitiveness in an effort

[5]For example, firm A is a competitor with firm B, but not with firm C. Whereas, firm B is a competitor with both A and C. Our approach instruments for firm B's effect on firm A through the effect of firm C's decision on firm B. The validity of this instrument is based on the fact that firm C does not work in a therapeutic area related to firm A, and thus the effect of firm C's IPO decision on firm A's IPO decision operates only via firm B. We discuss how this likely holds in our setting, and also demonstrate that our results hold even while ensuring that firms A and C do not have any overlap when considering a broader definition of therapeutic category.

to advance project development towards commercialization.

Our study relates to several literatures. Our analysis contributes to the literature examining competition and IPOs. Hsu et al. (2010), Chemmanur and He (2011), and Chod and Lyandres (2011) find that new offerings adversely affect existing firms within an industry in terms of operating performance, market share, and share price.[6] This suggests that transitioning to public equity markets confers competitive advantages to newly public firms to the detriment of other firms in the industry. The contribution of this study is that we show that competitive pressures from recent public offerings can influence peer IPO decisions. We also provide results consistent with competitive effects in other funding decisions, such as venture capital funding and being acquired, and examine how these decisions relate to IPO propensity. We are also the first, to the best of our knowledge, to show that IPO propensity is related to the degree of R&D competition, while the prior literature primarily focuses on competitive effects of product market competition.

The present study is also related to papers that have considered information spillovers from IPOs. Lowry and Schwert (2002) and Benveniste et al. (2003) find evidence consistent with follower firms benefiting from informational spillovers of earlier IPOs. We complement this literature by examining informational spillovers among direct competitors. We find that informational spillovers from IPOs do not seem salient among direct competitors, which suggests that information effects are more broadly shared at the market or industry level. A number of papers investigate the determinants of IPO propensity, such as Lerner (1994), Pagano, Panetta, and Zingales (1998), Brau, Francis, and Kohers (2003), Lowry (2003), Kim and Weisbach (2008), Chemmanur, He, and Nandy (2010), Gao, Ritter, and Zhu (2013), and Ewens and Farre-Mensa (2020). We contribute to this literature by being the first to show that IPO propensity is significantly related to the recent IPO of a direct competitor.

Our findings contribute to the small but growing literature on peer effects in capital markets, which has found that firm decisions (such as dividend increases or stock splits) tend to be related to the actions of industry peers (e.g., Reppenhagen, 2010; Tse and Tucker, 2010; Leary and Roberts, 2014; Kaustia and Rantala, 2015; Grennan, 2019; Foroughi, Marcus, Nguyen, and Tehranian, 2021; Seo, 2021).

We show that peer effects are present in IPO propensity, as well as in funding propensities more generally. Moreover, we examine peer effects in the decisions among *privately* held companies, while the extant literature has largely focused on public firms. In addition, our

[6]Relatedly, using structural estimation, Spiegel and Tookes (2020) find that both fluctuations in industry conditions and a competitor's IPO contribute to the decrease in the performance of public rivals following a competitor IPO within an industry. However, the results concerning the former effect are stronger.

precise characterization of a firm's competitors allows us to distinguish effects arising from R&D competitors and product market competitors, whereas the extant literature generally defines peers at the industry level or by identifying product market competitors.[7] Relatedly, this study contributes to the literature that examines similarity in the sequential actions of agents in capital markets. These include herding among institutional investors (e.g., Cai, Han, Li, and Li, 2019), sell-side security analysts (e.g., Welch, 2000) and firm disclosures (e.g., Tse and Tucker, 2010). We find similarity in the IPO decisions of closely related firms and that competitive concerns contribute to this similarity.

Finally, as one of the mechanisms that we explore is an informational channel, this study relates to the literature that examines information externalities of peer disclosure and its effects on firm characteristics and decisions. These studies have found that greater peer disclosure influences a firm's share price (e.g., Han, Wild, and Ramesh, 1989), liquidity (Bushee and Leuz, 2005), investment (e.g., Badertscher, Shroff, and White, 2013), and cost of capital (Shroff, Verdi, and Yost (2017)). In a similar vein, another stream of literature has examined how firms respond to or learn from peers in other forms, such as through their financial restatements (e.g., Gleason, Jenkins, and Johnson, 2008), share prices (Foucault and Fresard, 2014), and takeover threats (Servaes and Tamayo, 2013).

2 Conceptual framework

In this section, we discuss the conceptual underpinnings for our main predictions. Firms decide to go public when the benefits of doing so outweigh the costs. Our conceptual framework revolves around the notion that observing the IPO of a direct competitor affects the costs or benefits of going public (or the benefits of remaining private). For example, a direct competitor's IPO can positively change the *marginal benefit* of going public, which would lead to an increase in IPO propensity. Similarly, the IPO decision of a competitor may increase the marginal cost of staying private. We focus on considerations that specifically involve observing the IPO of a direct competitor. The first channel we discuss—competition—hypothesizes that the going-public decision confers competitive advantages to newly public rival firms, and hence the marginal benefit of staying private for competitor firms decreases. We next discuss an informational channel, whereby the IPOs of competitor firms can reveal important information that can be used in the IPOs of similar firms, thus lowering the marginal IPO

[7] A few papers (e.g., Foucault and Fresard, 2014) use the Hoberg and Phillips (2016) method to identify product market competitors through textual analysis of firm 10-K filings. Kaustia and Rantala (2015) use common analyst coverage to identify peer firms.

costs of similar firms.

2.1 Competition channel

The transition to public equity markets carries a number of competitive advantages to newly public firms relative to their still-private counterparts. An IPO generally brings a substantial cash infusion for the issuing firm. Unlike debt, equity capital has few strings attached and allows managers flexibility in their investment decisions. As a result, firms can expand their project portfolios by exploring new drugs or acquiring rival products. Moreover, the influx of capital allows firms to devote greater resources to existing drug-development projects. This can potentially speed up project completion, allowing an eventual product to be launched and hit the market more quickly. This boost to development is a potential advantage from going public that is particularly salient among R&D competitors, as being the first in the commercialization of a new drug can lead to patent and marketing exclusivity benefits.

Second, the bookbuilding and marketing process of the IPO allows the issuing firm to help gain the attention of institutional investors. This can be useful in later periods if the firm seeks external finance through follow-on equity issues.[8] These potential effects, as well as those discussed above, all confer competitive advantages to a newly issued firm. As a consequence, private firms are at a relative disadvantage when a direct competitor goes public. In order to remain competitive, a firm may increase its propensity of going public after observing a direct competitor undertake an IPO. In other words, the marginal benefit of remaining private *decreases* upon the IPO of a rival firm (or, equivalently, the marginal benefit from going public increases following a competitor's IPO).

We note that, while the IPO of a competitor may result in a loss of competitive advantage, the transition to public equity markets can also be costly. For example, going public may exacerbate agency frictions among management and strengthen short termism (e.g.,

[8]The IPO can confer additional competitive advantages to firms in other ways as well. Media coverage of the IPO may generate attention from retail investors (Engelberg and Gao, 2011), which can have profitable downstream consequences when products are taken to market. In particular, a greater media presence can help to familiarize the company among potential consumers (Stoughton, Wong, and Zechner, 2001; Demers and Lewellen, 2003) and draw attention to the company's products. This can be a significant advantage over private firms, which, due to their limited public financial disclosures, likely generate less media interest and thus less consumer awareness. Moreover, the recent certification from underwriters and enhanced regulatory scrutiny can be useful for obtaining debt financing and attracting investors (Chemmanur and Fulghieri, 1994; Hsu et al., 2010). The IPO can also improve liquidity, allowing pre-IPO investors to diversify and thus tolerate greater risk (Chod and Lyandres, 2011). In addition, a large literature has argued that external shareholders can improve corporate governance through better monitoring of management (e.g., Gompers, Ishii, and Metrick, 2003). However, we note that these advantages are potentially less applicable to biopharmaceutical firms that are engaged primarily in R&D at the time of their IPO, as, for example, the IPO may be long before they have any marketed drugs to consumers.

Stein, 1989). Relatedly, public firms are subject to greater public disclosure requirements, increasing a firm's proprietary disclosure costs (Guo, Lev, and Zhou, 2004; Aghamolla and Thakor, 2019). Private firms are more inclined to go public following a peer IPO if the increased benefit of going public (remaining competitive among rivals) is sufficiently high such that it outweighs the marginal cost. Hence, if the loss of competitive advantage from remaining private after a peer goes public is severe enough, this can lead to heightened IPO propensity.

In contrast to the above argument, it is also possible that observing a competitor's IPO has a *negative* impact on the IPO propensity of a peer firm. For example, the competitive advantage gained by a firm's competitor after going public could be so large that the focal firm shifts its focus and resources towards developing projects in other areas, which would thus delay the time to an eventual IPO. This is consistent with models of competition, whereby follower firms are discouraged from innovating if the distance to catch up to the competition becomes too large (e.g., Aghion et al., 2005).

2.2 Information channel

Peer IPOs may also affect a firm's IPO propensity through observational learning or information spillovers. In order to determine the initial price range when filing the IPO, the issuing firm and its underwriters must engage in costly information acquisition regarding the valuation of the firm prior to the filing (Benveniste et al., 2003; Hanley and Hoberg, 2010). Moreover, during the bookbuilding process, additional evaluative information is revealed from informed investors (Benveniste and Spindt, 1989; Hanley, 1993). In both cases, a firm that goes public generates new information that could be used by similar firms. For example, a competing firm can freeride off of the costly information production, revealed in the IPO prospectus and road show disclosure and in the market price, of a close peer when determining the price range of its IPO, thereby reducing its information gathering costs.[9] Likewise, an underwriter that recently handled an IPO may be better equipped and can more efficiently underwrite the IPOs of other similar firms if informational commonalities (such as the firms working in the same therapeutic category) are present. As a result, firms that observe a direct competitor's IPO may have a lower marginal cost when going public

[9]This is also noted by Benveniste et al. (2003): "[...] information production is costly and becomes a public good during the marketing effort [by issuing firms]" (p. 577), as well as by Hanley and Hoberg (2010): "If, instead, issuers and underwriters choose to invest less in premarket due diligence, then [prospectus] disclosure will have a higher exposure to standard rather than informative content, as more of the prospectus is likely to be 'copied' from other sources, such as recent and past industry IPOs" (p. 2823).

themselves, as they can save on costly information gathering and due diligence.[10]

Relatedly, informational spillovers from a competitor's IPO may be present in other forms. In particular, a competitor's decision to transition to public equity markets can be a positive signal regarding the IPO firm's project development. This can lead private peer firms that develop projects in the same area to positively update regarding the likelihood of success or an eventual breakthrough with their own projects. As such, private peers may be more inclined to expend additional resources towards development, which could amplify the propensity to transition to public equity markets for peer firms.[11]

A competitor's IPO can also convey important information regarding investor demand. Specifically, how the offering is received by investors and the market is valuable information for similar firms. A strong investor reception to the IPO may induce competing firms to go public to similarly capitalize on favorable investor sentiment (Ibbotson and Jaffe, 1975; Ritter, 1984; Lowry and Schwert, 2002; Aghamolla and Guttman, 2021). While previous studies have documented the effects of market-level sentiment on IPO volume, it is natural that such informational effects should be particularly salient for related firms whose projects are within the same area. For example, high initial returns of a peer IPO provides additional information to competing firms that investors have a strong appetite for firms developing drugs within that particular area. This can allow follower firms to set a higher offer price, thereby generating greater proceeds from the offering, after observing the IPOs of related firms. Relatedly, a poor market reception for a competing firm's offering may have the opposite effect and rather dissuade similar firms from going public.

The arguments above suggest that firms can receive an informational advantage to observing a direct competitor's IPO. We explore this channel as well as the competitive channel more thoroughly following the main result in Section 4.

[10]Theoretical investigation of information spillovers and strategic timing has also been considered in Persons and Warther (1997), Altı (2005), and Aghamolla and Hashimoto (2020). Relatedly, Benveniste et al. (2002) model underwriters bundling IPOs to save on information gathering costs, and Chemmanur and Fulghieri (1999) analytically consider the various tradeoffs in the going-public decision.

[11]Competitive pressures, as discussed previously, may also interact with the information spillovers noted here. For example, the increased likelihood of a breakthrough could lead still-private peers to go public in order to obtain more funding and stay competitive in the race towards commercialization.

3 Data and Empirical Methdology

3.1 Data

Our main data source is the Informa BioMedTracker (BMT) database, which provides data on private and public pharmaceutical and biotechnology firms in the U.S. The database contains granular information on each firm's drug project portfolio—details regarding each individual drug project that the firm is developing at any given point in time, the drug's phase in the FDA approval process at any point in time, the therapeutic indication category that the drug falls into, and the estimated likelihood of FDA approval.[12] BMT collects information from a wide range of sources, including company disclosures, regulatory filings, company websites, manager conference calls, and news articles. Thus, the database allows us to identify the full landscape of private firms in the biopharmaceutical industry, and in particular which firms are direct competitors, as we describe in more detail in the next section.

For each firm and each quarter in BMT from 2000 to 2016, we first identify all drug projects in the firm's portfolio.[13] This allows us to identify all therapeutic indication categories the firm operates in, which in turn enables us to identify the direct competitors of each firm in our sample. It also enables us to construct a score of outcome and control variables for each firm-quarter observation based on that firm's drug portfolio, which we describe in the next section.

In order to identify when a firm has undertaken an IPO, we match our dataset from BMT to Compustat. We drop any firm that had gone public prior to 2000. This enables us to examine whether a given firm decides to go public in a given quarter, and also whether any of the firm's competitors have gone public over the past four quarters.

This selection criteria yields a sample of 2,570 private firms with 74,992 firm-quarter observations, and a total of 237 IPOs from 2001 to 2016 for which we estimate our IPO propensity regressions. We end our sample period in 2016 because this is the last year for which our data extract has full coverage; however, in additional tests using a constructed sample based on limited data through 2020 and including a total of 432 IPOs, we find very similar results. We note that our inclusion of IPOs is restricted to firms that have clinical

[12] BMT provides estimates of the eventual likelihood of FDA approval for each drug, which utilize historical data combined with analyst-updated estimates based on events such as trial results.

[13] This is the time frame for which BMT has the most complete coverage. We drop projects for which there is missing information regarding the project's therapeutic category or likelihood of approval. Our conclusions are robust to more stringent selection criteria, such as excluding exploratory/preclinical projects or projects that are near approval.

trial data in BMT, as these data are needed for our specifications. This excludes firms that do not (or are yet to) engage in clinical trials of drugs in the U.S. This also excludes companies that may be classified as biotech/pharma firms according to some industrial classification systems but do not conduct trials, such as firms providing consulting or safety evaluation services, manufacturing services, and some medical device firms.

We also obtain additional balance sheet information from the Compustat Quarterly database, as well as data from SDC Platinum, to explore additional outcomes for IPO firms. We supplement this data with hand-collected data on underpricing and proceeds for the IPOs in our sample from Bloomberg, as well as hand-collected data on IPO filing dates from Securities and Exchange Commission (SEC) filings, in cases where these data are missing in SDC Platinum. Finally, in order to explore other private firm funding peer effects in our final analyses, we collect acquisition data from SDC Platinum and venture capital funding data from the VentureXpert database, and we manually match these transactions to our sample firms in BMT.

3.2 Empirical Methodology

Our main empirical tests explore how a private firm's IPO propensity is affected by a peer firm's decision to go public. In order to examine this, we first identify a biopharma firm's peers. For any given firm i, we identify a peer firm j as a firm with a drug project in development that is in the same granular therapeutic indication category as a drug project in firm i's project portfolio. There are 669 unique therapeutic indication categories that are provided by the BioMedTracker database. Examples of these indication categories include "Sickle Cell Anemia", "Cryptococcal Meningitis (Antifungal)", and "Acute Myelogenous Leukemia (AML)". In a given year in our sample, a firm has a median of 2 indication categories in its drug portfolio.

The granularity of these indication categories allows us to overcome concerns—inherent to a broader classification of peers—that any group of particular firms may not directly compete with each other. For example, two firms that are in the same 4-digit SIC industry such as the pharmaceutical sector (SIC code 2836) may develop products that are entirely different from one another; for instance, an aspirin pill manufacturer will not compete against a cancer drug manufacturer. The same concern applies to more narrow definitions of competitors—for example, two firms that develop cancer drugs may not directly compete against each other, since there are many different types of cancer that involve very different biological pathways to treat. Instead, our definition of peers is detailed enough to exploit differences in the specific

type of cancer (e.g., thyroid cancer or bone cancer). In additional tests, we demonstrate how our granular definition retains explanatory power even when controlling for broader peer classifications.

Another important advantage to this approach is that it allows us to solve the issue of simultaneity, or reflection, which is a major identification challenge in estimating peer effects. The reflection problem, as described by Manski (1993), refers to the inability to distinguish between the different effects that may influence peer behavior. For example, in the context of our setting, a firm may be going public either due to the IPO of a rival (an action), or due to some other (unrelated) characteristic of the firm's peer group.[14] Manski (1993) shows that, in the standard peer effects model, the primary regressor of interest (peer actions) is linearly dependent on the other regressors. As a result, identification of the peer action effect fails and cannot be distinguished from the other effects. In other words, reflection is a particular kind of simultaneity in which there are fewer equations than unknowns.

An important assumption for the reflection problem to hold is that all peers within a group have the *same* set of peers, and hence the peer actions regressor does not vary among peers within the same group. In contrast, our construction of peer groups, based on each particular firm's project portfolio, is *firm-specific* and results in the vast majority of firms having a *distinct*, yet partially overlapping, set of peer firms. For example, if firms i and j are peers to each other, then their peer groups are said to only partially overlap if their peer sets do not exactly coincide (excluding i and j). As shown by Bramoullé, Djebbari, and Fortin (2009), De Giorgi et al. (2010), and Laschever (2013), the use of partially overlapping peer groups, or peer group heterogeneity, completely solves the reflection problem.[15] This is because the action of firm i's distinct peers, which do not overlap with firm j's peer group, allows an identification of the peer effect for firm i, relative to firm j which did not experience a peer effect. In contrast, if firms i and j did *not* have distinct peer groups (and thus their peer groups perfectly overlapped), then it would not be possible to separately identify if an observed outcome was due to the actions of the peer or, say, characteristics of j and other firms. More simply, the presence of partial overlap in peer groups allows there to be enough equations relative to unknowns, which makes it possible to identify all of the parameters in the model.

Hence, our definition of peer groups alone allows us to resolve one of the major endogeneity challenges in estimating peer effects. Additionally, heterogeneity in peer groups provides

[14]Manski (1993) refers to the response to peer actions as endogenous effects and to the response to peer characteristics as exogenous, or contextual, effects.

[15]See De Giorgi et al. (2010, p. 254-255); Bramoullé et al. (2009) solve for the general case.

a natural instrument—peers of peers—for instrumental variables estimation in order to help alleviate other concerns regarding unobserved common shocks and endogeneity.

With this definition of peer in hand, we run the following OLS regression at the firm-quarter level:[16]

$$IPO_{i,t} = \beta_0 + \beta_1 Peer\,IPO_{i,[t-4,t-1]} + \alpha' X_{i,t-1} + \theta' Y_{i,t-1} + \gamma' Z_{t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \quad (1)$$

In Eq. (1), $IPO_{i,t}$ is a dummy variable that takes a value of 100 if firm i has undertaken an IPO in quarter t, and zero if it remains private in quarter t. A firm is removed from our sample once it has gone public. $Peer\,IPO_{i,[t-4,t-1]}$ is our main explanatory variable, and is defined as a dummy variable that equals one if firm i has a peer private firm that has undertaken an IPO in the previous four quarters, and zero otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ therefore exploits firm-specific definitions of peers based on firms that work within common therapeutic categories, and indicates whether one of these firms has gone public.

We include a number of control variables in our specifications, represented by the vector $X_{i,t-1}$. These include $LOA_{i,t-1}$, the mean (lagged) likelihood of eventual approval of firm i's drug projects, which controls for the risk of a firm's project development portfolio. LOA controls for both differences in the inherent risk of developing in different indication areas (for example, cancer versus hematology) as well as differences in the phase of research of drugs in the firm's development portfolio (with late-stage drugs having a higher likelihood of approval than earlier-stage drugs). However, we also explicitly control for late-stage research, as noted below.

The variable $Num\,Drugs_{i,t-1}$ is the total (lagged) number of drugs in firm i's project portfolio, as a measure of firm size. $Age_{i,t-1}$ is the lagged age of the firm, in quarters. $Late\,Stage_{i,t-1}$ is the lagged number of projects in the firm's development portfolio in Phase 3 or above, to control for late-stage research being more capital intensive. $Y_{i,t-1}$ represents a vector of mean peer firm covariates, which include average lagged LOA, $Num\,Drugs$, Age, and $Late\,Stage$ of firm i's peer group; including these variables allow us to condition on the action of a firm's peer group (IPO) while controlling for the characteristics of the peer

[16]We estimate a dynamic OLS model as our main specification, rather than a nonlinear model such as probit or logit, because an OLS model permits us to include fixed effects, thus allowing us to estimate effects controlling for time-invariant firm heterogeneity as well as common shocks in each time period. Prior literature (e.g., Neyman and Scott, 1948; Greene, 2004) has established that estimation results from nonlinear models (e.g., probit and logit) with fixed effects are difficult to interpret because the coefficient estimates are biased and inconsistent, a problem that is exacerbated when including interaction terms (e.g., Karaca-Mandic, Norton, and Dowd, 2012). However, for robustness, we demonstrate that our results hold when we run our main tests using hazard, probit, and logit specifications.

group. Z_{t-1} represents a vector of time-series control variables to control for overall market conditions (such as "hot" IPO markets), and includes the returns on a number of stock indices (the S&P 500, Nasdaq, and NYSE ARCA Pharma and Biotech indices) as well as the total number of IPOs in the biopharma sector for that period. Finally, μ_i and η_t are firm and quarter-year fixed effects, respectively. With the inclusion of firm and quarter-year fixed effects, the interpretation of Eq. (1) is that we are comparing the change in IPO propensity when a firm observes a peer going public, relative to the case when no peer firm has gone public, holding other things constant.

We note that quarter-year fixed effects account for any hot market effects where IPO volume is unusually high. In particular, time fixed effects account for that period's level of market and industry returns and the total number of IPOs. However, as a robustness test, we include these variables as control variables in another specification that does not include time fixed effects (when time fixed effects are also included, these variables are completely absorbed). The inclusion of fixed effects implies that we are isolating the change in the firm's propensity to go public after observing the IPO of a direct competitor.

Table 1 provides the summary statistics for our sample. The mean of $IPO_{i,t}$ is 0.309, indicating that the overall sample propensity to do an IPO for a firm in a given quarter is 0.309 percent. $Peer\,IPO_{i,[t-4,t-1]}$ has a mean of 0.447 but a median of 0.000, which suggests that while the majority of firms do not observe one or more peer firms going public in a given four-quarter period, a substantial number of firms do observe a peer IPO. We will further exploit some of this heterogeneity in our empirical tests. $LOA_{i,t}$ has a mean of roughly 23 percent, indicating that the average firm has a mean drug approval likelihood of 23 percent. A given firm has a mean of roughly 9 drugs but a median of 2 drugs, suggesting that there is dispersion in the size of firm drug portfolios, which we control for in the empirical specification. Finally, the median firm in our sample is 5 years old and does not have any late-stage projects in development.

4 Results

4.1 Peer Effects in IPO Propensity

The estimation results for our main regression (1) are provided in Table 2. Column (1) provides results with no controls or fixed effects. The next two columns provide the results when including controls (column (2)) and controls and firm fixed effects (column (3)). For parsimony and to increase readability, we do not report coefficient estimates for the control

variables in our tables; these estimates are provided in the Online Appendix. Column (4) adds the lagged returns on a number of equity indices—the S&P 500, Nasdaq, NYSE ARCA Pharma, and NYSE ARCA Biotech—in order to control for "hot" markets, which have been shown previously to affect IPO propensity. Along similar lines, we also add the number of IPOs that occurred in the biopharma industry during the previous quarter as controls. Column (5) adds firm and quarter-year fixed effects, the latter of which absorbs all variation of the time-series controls from column (4). Finally, column (6) includes both firm and quarter-year fixed effects and controls (the firm's portfolio LOA and size), while column (7) additionally includes the average covariates of firm i's peer group as controls.

Across all of the different specifications, the coefficients for $Peer\,IPO_{i,[t-4,t-1]}$ are positive and significant. In particular, the column (7) magnitude indicates that firms which observe a peer IPO increase their propensity of going public from a baseline rate of 0.31 to 0.44 percent per quarter relative to other firms. This suggests that observing a peer going public increases a given firm's IPO propensity in a given quarter by roughly 40 percent relative to the population of private biopharma firms. Put differently, when compared to the baseline IPO rate at the firm-quarter level for firms that do not observe the recent IPO of a direct competitor, this represents a roughly 62 percent increase in IPO propensity from a rate of 0.20 percent to 0.33 percent.[17] These results provide evidence consistent with the hypothesis that observing a direct competitor go public has an influence on a private firm's propensity to go public, even controlling for previously-documented effects, such as hot markets, that apply broadly to all firms within an industry.

We note that the inclusion of time fixed effects only marginally increases the R^2 after accounting for firm fixed effects. This indicates that the change in IPO propensity, conditional on a given firm, is not well-explained by common shocks that affect all firms in a given period. This is likely due to the low probability of going public for a given firm, since most firms stay private in a given quarter. Furthermore, for firms that never go public, the explanatory power of these time fixed effects are subsumed by the firm fixed effects, from which almost all of the explanatory power comes from. When excluding firm fixed effects but including time fixed effects, we obtain an R^2 of roughly 0.4%. This is consistent with it

[17] In particular, 0.31 percent is the unconditional propensity for a firm to go public across our sample, and 0.20 percent is the propensity for a firm to go public conditional on it not observing a peer IPO. We also run a specification, Appendix Table A1, where we interact our main explanatory variable $Peer\,IPO_{i,[t-4,t-1]}$ with the number of unique therapeutic indication categories that a firm operates in. We find that our effect becomes weaker for firms that operate in more areas, which is consistent with the effect being stronger if a firm has fewer peers. Our results also do not seem to be driven by strategic concerns related to venture capital ownership; in supplemental tests explicitly controlling for ownership by each individual VC firm in our sample, we still find the same results.

generally being difficult to predict if and when a particular firm will go public, although we demonstrate that the actions of close rival are a significant determinant of this decision. We also note that the firm fixed effects introduce a look-ahead bias, since they inherently use information that a given firm will go public at some point (and roughly 10% of our sample ever goes public). Since we are focused on the problem of whether a given firm goes public this quarter or some other quarter, this look-ahead bias is not an problem for our setting. Furthermore, as Table 2 shows, our results are robust to not including firm fixed effects.

In Table A2 of the Appendix, we run our main specification using a constructed sample based on limited additional data through 2020, which includes a total of 432 IPOs.[18] With this updated sample, we find very similar results, indicating that our results hold when including the more recent period with additional IPOs.

While our main specification is run at the quarterly level, we also consider a related specification at the firm-year level, replacing our main explanatory variable with $Peer\,IPO_{i,t-1}$, defined as an indicator that equals one if firm i has a peer private firm that has undertaken an IPO in the previous calendar year and zero otherwise. The results from this specification are reported in Appendix Table A3. The results are consistent with that of our main specification. In particular, the yearly estimates imply an increase in IPO propensity of 67 percent, from an unconditional baseline propensity to go public of 1.22 percent per year to 2.04 percent per year. We note that all of our subsequent tests are also robust to being run at the firm-year level.

An alternative to our main specification is to run our tests using a hazard model, with the "failure" event being that a private firm has undertaken an IPO in a given year. In Panel A of Appendix Table A4 we check whether our results are robust to doing so by running a Cox proportional hazard model. For the specifications, the hazard ratio is above 1 and is significant, indicating that firms are more likely to go public following the IPO of a direct competitor. Panel B of Table A4 shows that we find similar results when we estimate probit and logit models.[19]

[18]We construct the 2017–2020 sample using data on all project portfolio updates for the firms that went public from 2017 to 2020, and data on new trial initiations (allowing us to identify new private firms that entered). For projects in development for which we do not have updates for, we assume that the drug project status is the same as it was in 2016.

[19]In Appendix Table A5, we run a standard placebo test in peer effects settings, where we randomly assign firms to different peer groups, and see if our effects are due to random noise. We do not find any effect when we do so.

4.2 Degree of Competition

We next turn to a deeper exploration of the channels underlying our effects. Peer effects in IPOs may operate through a number of different channels. As discussed above, one is a competitive channel—firms may follow their peers in going public to keep up with their rivals and advance or expand project development, as well as to not miss out on the competitive advantages inherent in going public, such as continued access to equity markets or potentially enhanced corporate governance through outside shareholders (Hsu et al., 2010). Another is an informational channel—seeing a peer go public may provide informational benefits that lower the cost of going public or signal positive information about the firm's prospects (Benveniste et al., 2002; Aghamolla and Guttman, 2021).

In this section, we further explore the competitive channel. At a basic level, if firms are making their decisions to transition to public equity markets because of competitive reasons, then we should see a stronger effect for firms that face a greater degree of competition. In order to test whether this is the case, we construct a measure of the amount of competition that a firm's drug portfolio faces at any given point of time. More specifically, we calculate a concentration index at the therapeutic category-level to measure how concentrated a given therapeutic category is in any quarter-year t. In particular, if the projects being developed in a certain therapeutic category are dispersed among multiple firms, then this category is *less* concentrated and thus *more* competitive. Likewise, if projects in development for a given category are concentrated in a small number of firms, this implies that the category is *less* competitive.[20] Then, for each firm i in each quarter-year t, we create $Avg\,Ind\,Concen_{i,t-1}$ as the mean concentration across firm i's drug indication categories. (We drop subscripts in the discussion for expositional ease.)

Table 3 provides our estimation results when segmenting our sample based on whether a firm faced above-median competition (low $Avg\,Ind\,Concen$, column (1)) or below-median competition (high $Avg\,Ind\,Concen$, column (2)). For firms that faced a higher degree of competition, the effect of observing a peer go public on a firm's IPO propensity is positive and significant, while it is insignificant for firms that faced a lower degree of competition. In column (3), we estimate the full sample but interact $Avg\,Ind\,Concen$ with $Peer\,IPO$, and we find consistent results—the effect of $Peer\,IPO$ on IPO propensity is stronger for firms that have lower levels of $Avg\,Ind\,Concen$ (i.e., higher levels of competition). Overall, the results suggest that our main effects are centered on firms that face the greatest degree

[20] This is calculated in the same way as a Herfindahl-Hirschman index (HHI), but in contrast to typical Herfindahl measures, which utilize sales data, we calculate this based on the number of actively developed projects.

of competition, which is consistent with competitive effects being an important mechanism through which peer effects in IPOs operate.

As an additional test of this channel, we consider the competitive distance between the focal firm and the competitor. Specifically, under the competitive channel, firms that are in tighter competition to bring their products to market should be more inclined to go public following the IPO of a peer. In contrast, the focal firm may have less incentive to go public after the competitor's IPO if the competitor is sufficiently far ahead of the focal firm in terms of project development. To measure competitive distance, we utilize our data on likelihood of approval (LOA), which captures both differences in the stage of development that a firm is at and also whether the prospects of a firm's drugs are better/worse than those of comparable drugs at a given stage. We therefore define competitive distance, $Distance$, as the mean LOA of a firm's competitors that went public over the previous four quarters minus the LOA of a focal firm's project portfolio (multiplied by 100 to express as percentage points). A higher $Distance$ thus implies that a focal firm is further behind its IPO peers. We then interact our $PeerIPO$ explanatory variable with $Distance$ to see if the IPO peer effect is dampened when the peer is ahead. We see in Table 4 that, while observing a peer IPO increases the propensity to go public, an increase in $Distance$ (i.e., the IPO peer being further ahead than the focal firm) weakens this effect. In particular, the estimates indicate that observing a peer go public increases IPO propensity by 0.12 percent per quarter, but a one standard deviation increase in $Distance$ (roughly 18 percentage points) reduces this effect by 0.08 percentage points per quarter. Collectively, the results suggest that firms go public when they are in close competition with their rivals, but are less inclined to do so when the rival is out of reach, consistent with models of competition (e.g., Aghion et al., 2005).

4.3 Information Channel

We now further explore the extent to which the increase in IPO propensity following a direct competitor's IPO is driven by informational spillovers. As discussed in Section 2, there may exist information externalities from a peer firm's IPO that could lower the cost of going public for follower firms (Benveniste et al., 2003). The evaluative information produced by a peer firm and its underwriters could lower the costs of information acquisition for related firms that go public. This may increase a firm's IPO propensity as the marginal cost of going public may be lower after observing a peer IPO (i.e., firms can freeride on the evaluative research produced by their peers). Likewise, the market reception to a peer offering may

be indicative of how the offerings of similar firms will be received by investors (Lowry and Schwert, 2002). A strong investor reaction may induce other firms to capitalize on the positive sentiment for firms developing drugs in that category.

To gain some insight on this channel, we examine the IPO outcomes for firms that go public in the four quarters after a peer firm's IPO compared to other firms that go public but *not* following a peer firm. The reasoning is, if the increase in IPO propensity is information driven, firms that go public in the footsteps of a peer can take advantage of the information produced, which may be reflected in their IPO outcomes. We construct a variable, $PeerIPO_i^F$, that takes a value of 1 if firm i has gone public in the four quarters following a peer firm's IPO, and 0 if a firm has gone public but did not observe a peer IPO. Thus, our tests compare firms that went public following a peer to other IPO firms.

We examine three IPO outcome variables. First, we consider the amount of time between the filing date and the IPO completion date; information spillovers from a peer IPO should expedite the IPO process for a follower firm as there may be less effort and time necessary for information gathering and due diligence during the bookbuilding process. Second, we examine the level of underpricing; follower firms can use the evaluative information generated by a peer to more accurately price the offering, resulting in less money left on the table (i.e., lower underpricing). In line with this argument, we also consider IPO proceeds.[21]

The results are presented in Table 5. We find that none of the estimated coefficients on the above outcomes are statistically different from zero. We similarly examine whether observing the market reception of a peer firm influences IPO propensity. We examine whether firms increase their IPO propensity following a positive investor reaction to a direct competitor's IPO (measured as the level of initial returns or underpricing of the IPO). The results are presented in Appendix Table A6 and are not significant. In a similar vein, we additionally consider a competitor's post-IPO stock returns over a longer horizon (from the IPO date to the end of that quarter), and find consistent results (Table A7). Overall, the results provide little support for the hypothesis that informational spillovers are driving the increase in IPO propensity. We note that the lack of significance here contrasts somewhat with the prior literature (e.g., Lowry and Schwert, 2002; Benveniste et al., 2003); this suggests that information spillover effects are more salient at the market or industry level. Indeed, the presence of time fixed effects eliminates any information spillovers regarding sentiment or

[21]Data for these variables come from SDC Platinum; we supplement this with hand-collected data from news sources and SEC filings in the cases where the data are missing in SDC. Underpricing is defined as the first day's trading return relative to the IPO offer price. Proceeds are in real 2016q4 dollars to adjust for inflation.

information production that are shared at the industry level.

4.4 R&D and Product Market Peers

We next examine whether our effect differs depending on the *type* of peer. In particular, since biopharma companies operate in an innovative sector, research and development for new projects is essential to their continued operation. Thus, one natural definition of a peer is an R&D competitor to a given firm—another firm that is actively researching a project (i.e., has a drug in the clinical development process) in a given indication area. However, an alternative definition of a peer focuses on the product market—another firm that has an approved drug (that is marketed to consumers) in a given indication area. Here, we explore whether the distinction between these two types of peers, based on drugs in development or approved drugs, matters.

To examine whether this distinction matters, we split our main variable, $Peer\,IPO_{i,[t-4,t-1]}$, into R&D competitors, $Peer\,IPO^{R\&D\,Peer}_{i,[t-4,t-1]}$, and product market competitors, $Peer\,IPO^{Product\,Peer}_{i,[t-4,t-1]}$. (We again drop subscripts in the discussion for ease of exposition.) The variable $Peer\,IPO^{R\&D\,Peer}$ denotes whether an R&D peer firm has undertaken an IPO, with the peer firm being defined as having a *non-approved* drug project currently under development in the same therapeutic category. In contrast, $Peer\,IPO^{Product\,Peer}$ denotes whether a product market peer firm has undertaken an IPO, with the peer firm being defined as having an *approved* drug in the same therapeutic category.

Table 6 provides the results examining these different types of peers. Column (1) shows that our previous results hold when examining R&D peers—the coefficient on $Peer\,IPO^{R\&D\,Peer}$ is positive and significant, with a similar magnitude as our main result. Interestingly, we find that when examining product market peers—as column (2) shows, $Peer\,IPO^{Product\,Peer}$ is insignificant, indicating that firms are not any more likely to go public after observing a firm with an approved product in the same therapeutic area go public. Column (3) includes both measures in the same regression, and confirms that these results continue to hold. However, we note that fewer firms are product market peers (45 firms) in our sample relative to R&D peers (214 firms).

The results in Table 6 are consistent with the notion that competitive effects help drive the decision to go public after seeing a peer do so, but that the relative competitive distance between the firms matters. After seeing a peer firm with a project in development in the same area go public, it may behoove a given firm to follow suit because they are able to effectively compete (given their own drug in development) with the peer firm after also

going public themselves. In contrast, after observing a peer firm that has an approved drug go public, the gap between the peer firm—which is able to take advantage of the additional benefits of going public along with the marketing exclusivity granted by FDA approval—and the given private firm may be so large that the private firm may decide that it can no longer compete with its peer. This effect is consistent with R&D competition models (e.g., Aghion et al., 2005), which predict that increased competition may increase innovation when firms are "neck-and-neck" (i.e., the gap between them is relatively close), but that the effect is negated if firms perceive that the leader is too far out of reach.

4.5 Outcomes following Peer IPOs

Peer IPOs compared to other IPOs

We additionally examine newly public firms' performance following the IPO decision. This allows us to examine whether IPOs that follow peers are quantitatively different from other IPOs (e.g., "leaders"), which may affect the interpretation of our results. In Table 7, we test ex post performance by restricting our sample to the IPO quarter and the subsequent four quarters of data for firms that have gone public, and examining a variety of accounting, project, and IPO outcomes (the results are qualitatively similar for alternative time windows). As in Section 4.3, we use the variable $PeerIPO_i^F$, that has a value of 1 if firm i has gone public following a peer firm's IPO in the prior four quarters, and 0 if a firm has gone public but did not observe a peer IPO.

In Table 7, we examine the effect for a number of accounting variables: size (total assets), profitability (return on assets, ROA, measured via net income scaled by lagged assets), capital expenditures (capex), cash holdings, debt, R&D expenditures, and sales.[22] We also explore LOA and $Num\,Drugs$ to examine whether there are any significant changes in firms' project portfolio characteristics.[23] Across all accounting variables (with the exception of debt, which is marginally significant) and all project outcomes, there is no significant difference between firms that went public after observing a peer and firms that went public not

[22]Capex, cash, debt, R&D expenditures, and sales are each scaled by total assets. These variables and profitability are winsorized at the 1% level.

[23]Since $PeerIPO_i^F$ is a cross-sectional variable, we do not include firm fixed effects since that would absorb all of its variation. We include lags of $\log(TA)$, $Capex$, $Cash$, $Debt$, $R\&D$, $Sales$, LOA, $Num\,Drugs$, Age, and $Late\,Stage$ as controls in each of the regressions. We note that the specifications exploring LOA and $Num\,Drugs$ include lagged values of these variables as controls. While this can help to ameliorate the autocorrelation that is present in these variables, it can potentially introduce bias (e.g., Nickell, 1981). In untabulated tests, we re-run these regressions to account for this bias using the specifications of Anderson and Hsiao (1982) and Arellano and Bond (1991). We obtain very similar results when we do so, indicating that this potential bias likely does not affect our estimates.

observing a peer. This suggests that follower firms are not significantly different from their non-follower counterparts after the IPO, and furthermore do not seem to lose a competitive edge relative to the leaders.

Peer IPOs compared to Firms that Stayed Private

We next examine project outcomes for IPO firms following peer IPOs compared to firms that stayed private following peer IPOs. The idea is that, if firms are going public due to competitive pressures, firms that go public following peer IPOs should have a performance advantage compared to firms that did not go public following the IPO of a direct competitor. As discussed in Section 2, one of the main competitive advantages from going public is the equity financing raised that can be used to fund investment. We thus expect that performance, in terms of project outcomes, should be stronger for firms that went public following a peer relative to those that continued to stay private after observing a peer IPO.

In order to explore whether this is the case, we construct a variable $\widetilde{PeerIPO}_{i,t}$ at the firm-quarter level that takes a value of 1 if a firm has gone public following a peer firm's IPO that occurred up through quarter $t-4$, and 0 if a firm stays private in quarter t after observing a peer go public.[24] We then look at the impact of this on the company's overall likelihood of project approval (LOA), the number of drugs in the company's project portfolio ($Num\,Drugs$), the number of indications in the company's project portfolio ($Num\,Indications$), and the number of early trial initiations, which includes new pre-clinical trials as well as successful transitions into Phase 1 trial testing.

Table 8 provides the results. As the table shows, compared to firms that stayed private after observing a peer go public, firms that go public following peers show no significant difference in terms of LOA. However, these firms exhibit an increase in the number of drugs and indication categories in their portfolio, and an increase in the number of new early-stage trials that they undertake. This provides evidence that is consistent with an improvement in outcomes, allowing continued investment activity by firms going public following competitors, compared to those that decide to remain private after observing a peer IPO.[25]

[24] We define this variable to switch on for this time frame to be consistent with the tests in Table 5, and in order to account for the possibility that changes in firms' project portfolios may manifest themselves only after a delay.

[25] We note that the initiation of new, early-stage projects will generally have a negative impact on a firm's LOA due to the greater risk inherent to early-stage development, which may explain why we do not find a significant difference in LOA in Table 8.

5 Robustness

In this section, we examine robustness of our main results. We first consider a specification with additional fixed effects. We then briefly discuss an instrumental variables specification, with additional details provided in the Online Appendix.

5.1 Additional Fixed Effects

A potential concern with our results is that they are driven by some characteristics or shocks that are common to certain groups of firms, but unrelated to the peer IPO channel. For example, operating in certain indication categories may make firms more likely to go public—if drugs in a given indication area tend to be more profitable than other areas, then firms operating in those areas may have a higher propensity to go public. Alternatively, a shock, such as a breakthrough in cancer genome sequencing (such as CRISPR technology), might be positive news that induces a number of firms working in oncology to go public because of enhanced prospects.

While including firm fixed effects as well as the average likelihood of approval helps to control for these possibilities, we more directly attempt to control for this by saturating our main specifications with additional fixed effects. Specifically, we first add 669 indication category fixed effects that take a value of one if a firm has a project in a given indication category in a given year, and zero otherwise. This controls for time-invariant differences across indication categories in the propensity to go public.

We additionally add broader time-varying disease group fixed effects, which control for shocks in any particular year that are common to firms working in a given area. In particular, we utilize the ICD-10 classification system for diseases, which provides a hierarchy for diagnosing diseases that is used by medical professionals, and include ICD-10 block-by-quarter fixed effects. Since our shock is defined at the therapeutic indication category-year level, the most granular time-varying fixed effects we can include are at the ICD-10 block-by-quarter level.[26] With these additional fixed effects, our empirical specifications thus specifically identify the effects of an IPO in a narrowly-defined therapeutic category, controlling for any trends that more broadly affect firms operating in the industry or broader disease groups.

The results with inclusion of these fixed effects are provided in Table A8 of the Appendix.

[26] The ICD-10 classification system for our sample includes 160 "blocks". An example of an ICD-10 block would be "acute upper respiratory infections" (block J00-J06), in contrast to a specific respiratory infection that would be identified through the granular indication categories. We assign each drug in our sample to an ICD-10 block based on the disease that it targets.

As shown in the table, even when including each of these fixed effects, $Peer\,IPO_{i,[t-4,t-1]}$ remains strongly positive and significant in all specifications, with a very similar magnitude as in the main specification. This shows that differences between indication categories or common shocks that broadly affect disease groups are unlikely to be driving our results. Furthermore, these results provide evidence that our granular definition of peers has additional explanatory power over broader definitions of peers, as the ICD-10 block-by-quarter fixed effects would account for peer IPOs (based on ICD-10 blocks) that occurred in a given quarter.

5.2 Instrumental Variables Specification

Our previous findings suggest that common shocks or other omitted variables are not driving our results. Moreover, our definition of peer groups based on a firm's particular project portfolio implies that peer groups do not perfectly coincide for peer firms in our setting, which solves the Manski (1993) reflection problem. However, to further address the possibility of unobserved common shocks or other potential endogeneity or reverse causality concerns, we use an instrumental variables (IV) approach. Below, we provide a brief description of the empirical approach and results. Additional details are presented in Online Appendix A.

We exploit the fact that, since each firm faces a potentially distinct peer group based on its own project portfolio, the set of peer groups in our data do not fully overlap. Specifically, we instrument for the IPO of a focal firm's peer by using the previous IPO decision of a firm that is a peer to the IPO-firm, but that is *not* a peer to the focal firm.[27] For example, consider three firms: A, B, and C. Suppose that firms A and B are peers because they operate in the same therapeutic category, and firms B and C are peers because they operate in the same therapeutic category, but firms A and C are not peers because they do not have any overlap in their project portfolios. In order to instrument for firm B's propensity to do an IPO—which would be $Peer\,IPO = 1$ from firm A's perspective—we would use firm C's previous IPO decision. We note that it is common for a biopharmaceutical firm to operate in disease groups that are unrelated to one another.[28] Fig. 1 graphically depicts this strategy.

[27] De Giorgi et al. (2010) use a similar approach.

[28] As a specific example, Intercept Pharmaceuticals undertook an IPO in 2012. Intercept has a peer, Horizon Pharma, that also develops drugs in the same indication category ("Mucositis"; a condition characterized by inflammation and ulceration of the digestive tract). Horizon Pharma transitioned to public equity markets in 2011. Horizon, in turn, has a peer—Assembly Biosciences—that went public in 2010. Horizon and Assembly are peers because they both develop drugs in the indication category "Hyperparathyroidism" (over-activity of the parathyroid glands). However, Intercept and Assembly do *not* share any indication category in their project portfolios. Thus, Assembly's IPO decision would be used to instrument for Horizon's IPO, in order to estimate the propensity for Intercept to undertake an IPO.

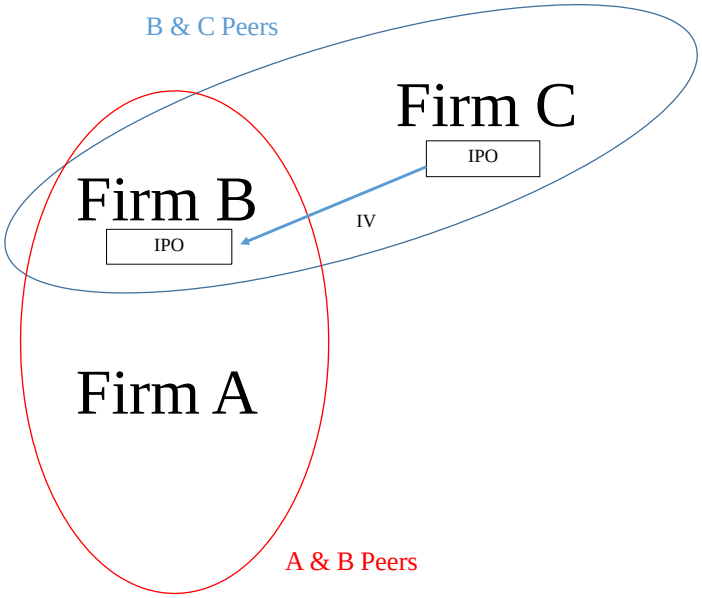

Figure 1: Graphical representation of the instrumental variables strategy.

We discuss further in Appendix A that this approach satisfies the exclusion restriction in our setting. We also consider a specification where we only instrument for peer IPOs using peers of peers that are *not* in the same broader ICD-10 block as the focal firm. This additional restriction ensures that peers of peers develop drugs in areas that are unrelated to the projects of the focal firm.

The results are included in Table A9 of the Appendix. The results continue to hold under both specifications of the IV, suggesting that our main results are not driven by endogeneity or reverse causality.

6 Peer effects in funding propensities

One of the channels we discussed in Section 2 is a competitive channel: firms that raise financing through an IPO can gain a competitive advantage over their peers, as the cash infusion from the IPO allows these firms to further develop their innovations and to potentially accelerate their product's time to reach the market. Accordingly, peers of these firms may be compelled to go public themselves in order to remain competitive.

In this section, we explore whether this argument generalizes to other kinds of funding decisions for private firms that may provide significant capital for the firm. In particular, financing raised by competitors through other funding opportunities may elicit a similar peer effect due to the competitive advantages of increased capital. One such avenue that

private firms can utilize is obtaining funding from a venture capital (VC) firm or from corporate venture capital.[29] Another avenue is selling the firm completely to a deep-pocketed firm.[30] Moreover, firms may use different avenues of funding in response to the increase in a competitor's capital. For example, a firm can raise VC funding, instead of going public, to attempt to remain competitive after the IPO of a close rival.

We therefore consider the hypothesis that the effect we document in Section 4 may hold more broadly for various kinds of funding opportunities, where firm decisions are driven by the new capital raised by their competitors. To examine this hypothesis, we extend our baseline setting to consider peer effects in funding propensities more generally, i.e., whether firms respond to the funding decisions of their direct rivals through potentially other kinds of funding decisions. In particular, we augment our baseline specification (1) to include both venture capital funding and selling the firm to a larger firm (i.e., being acquired):

$$Funding_{i,t} = \beta_0 + \beta_1 Peer\ Funding_{i,[t-4,t-1]} + \alpha' X_{i,t-1} + \theta' Y_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \quad (2)$$

In the above specification, the dependent variable, $Funding_{i,t}$, is equal to 100 if firm i went public, received VC funding, or was acquired in quarter t, and zero otherwise. Firms in our sample are dropped once they go public or are acquired by another firm. Relatedly, the main explanatory variable, $Peer\ Funding_{i,[t-4,t-1]}$, is an indicator equal to one if a peer of firm i, defined as in Section 3.2, goes public, raises VC funding, or is acquired in the previous four quarters. In our regressions, we first consider each funding channel individually—i.e., whether the peer action predicts the propensity of the *same* action—and then explore general peer funding effects via the combination of any of the three channels. Control variables and fixed effects are the same as in our main specification (1).

To provide additional texture to this analysis, we also consider whether the corporate

[29]The distinct advantages of obtaining financing from a venture capital fund include, for example, mentorship and strategic guidance from the VC general partners, as well as access to the VC partners' network. VC firms have also been documented to add value through improved governance and monitoring of their companies (e.g., Kaplan and Strömberg, 2004). Moreover, receiving VC financing itself can signal information to other investors, which can open the door for additional funding opportunities. Hence, venture capital financing can carry specific competitive advantages in addition to the capital raised, which may lead peer firms to more actively seek VC financing after a competitor has done so.

[30]Being acquired, or selling the company out to a larger firm, may also carry specific competitive advantages. Greater resources from the acquiring firm could allow the competitor to more quickly develop innovations, and the competitor also gains access to the acquirer's network. Moreover, there may be informational spillovers in selling out (similar to those of IPOs) that could influence peer behavior. For example, a competitor's high acquisition price may lead peer firms to seek such deals due to informational freeriding in the evaluation of the company, or due to the realization of high investor demand for similar projects, as discussed in Section 2.

actions of raising VC financing, being acquired, or going public by competitor firms influence the propensity for a *different* action by their peers shortly thereafter. For example, we explore whether a firm is more likely to obtain VC funding after observing a peer go public. This helps to disentangle and better understand the drivers of a peer effect in specification (2). Moreover, it is possible that these other funding opportunities have specific features or provide distinct advantages for firms, in addition to the capital raised, which may induce peer firms to take alternative actions.

6.1 Results

We present the results of specification (2) in Table 9. We begin by examining VC peer effects—whether a firm is more likely to obtain VC funding following a peer having received VC funding—in column (1). Our sample includes 2,899 firm-quarters for which a firm received VC funding. We find that the coefficient is insignificant, indicating that firms are not more likely to obtain VC funding after a peer does. However, in column (2), we re-define our $Peer\,VC$ and $VC\,Funding$ variables to switch on only for VC funding rounds that are above-median (the median funding round amount in our sample is $8 million). We find that firms are significantly more likely to raise above-median VC funding after observing a peer do so, indicating that peer effects manifest in VC funding only for large funding amounts. This suggests that the *scale* of funding matters—a small amount of VC funding may not provide a firm with enough of an edge to engender a response by a competitor, especially given the large costs of clinical development (e.g., DiMasi, Grabowski, and Hansen, 2016). In contrast, a larger amount obtained by a peer induces a firm to seek a comparable amount.

In column (3), we explore acquisition peer effects.[31] The coefficient on $Peer\,Acquired$ is positive and significant at the 5% level, and indicates that a firm is roughly 0.1 percent more likely to be acquired following a peer acquisition, an increase of 58% relative to the unconditional sample acquisition propensity in a given quarter. This suggests that firms react to a peer getting acquired in the previous four quarters by being more likely to get acquired themselves, and thus selling out generates funding peer effects. Column (4) looks at funding peer effects generally by considering whether a firm takes *any* funding action—either obtaining VC funding, getting acquired, or going public—in response to a peer raising funding through any of these actions. In line with the individual funding channel peer effects, general funding peer effects are significant, implying that firms are more likely to choose any of the three types of funding in response to a competitor receiving funding.

[31] We identify 231 firms in our sample as eventually acquired based on our acquisition data.

To examine the channels behind these results in more detail, in Table 10 we explore peer effects *across* the different types of funding decisions. Beginning with observing a peer obtain above-median VC funding in columns (1) and (2), we find that a firm is more likely to go public or be acquired in response. If a firm's competitor is instead observed to be acquired (column (3)), we find that the firm is *not* significantly more likely to obtain above-median VC funding. In contrast, a firm is more likely to go public after observing a peer be acquired. Finally, in response to a peer going public, a firm is significantly more likely to be acquired by a larger firm, but not significantly more likely to obtain above-median VC funding.

Taken together, these results are consistent with firms choosing an appropriate source of funding due to competitive pressures after a peer receives funding, and suggest a type of "pecking order" of peer funding effects based on the *magnitude* of the funding source. While VC funding is a prevalent funding source in the biotech/pharma industry, the typical capital influx that comes with a round of VC funding is much lower than that which comes with being acquired or going public. In our sample, the median VC funding round amount is \$8 million.[32] In contrast, the median IPO proceeds in our sample is \$61.1 million—for comparison, the median VC funding amount corresponds to the first percentile in terms of IPO proceeds. Similarly, the magnitude of capital access via being acquired is larger than VC funding since the acquirer is typically a much larger firm with deep pockets and thus can provide significant resources to advance drug development projects of the acquired firm. As an indication of this, the median M&A deal size in our sample is \$34.2 million, which corresponds to the 88th percentile of VC funding round amount.[33]

These funding magnitudes indicate that going public or being acquired are sufficient funding responses to overcome the competitive boost that a peer may have gotten from high VC funding. However, raising VC funding is generally a weak response to a competitor going public or being acquired, as it does not allow the focal firm to overcome a peer's competitive edge. Additionally, acquiring a substantial level of VC funding in itself can be difficult, as the median institutional VC fund size is only \$100 million (Gompers et al., 2020), and funds are disbursed across many invested companies. The results of Tables 9 and 10 are consistent with the notion that the scale of funding that a competitor raises matters. Moreover, the results suggest that firms are often willing to seek relatively larger funding sources compared to their peers in order to stay competitive.

[32]This is in line with a median funding round size of \$11 million across institutional VC firms (Gompers, Gornall, Kaplan, and Strebulaev, 2020).

[33]The importance of these relative funding sizes also aligns with the fact that development costs, even for a single drug, are large—see DiMasi et al. (2016), for example.

We additionally see that being acquired is a response to a competitor's increase in funding. This suggests that firms also utilize the resources of a larger firm to stay competitive. However, the coefficient magnitudes and significance in the tables suggest that firms are relatively more likely to choose an IPO over selling out as a competitive response to a peer's funding decision. This provides evidence that IPO peer effects are distinctive compared to other funding sources due to the magnitude of funding—both direct IPO proceeds and access to secondary equity markets—which allows firms to more effectively overcome competitive pressures in an effort to cross the finish line for commercialization. IPOs also have distinct advantages in terms of exposure to both institutional and retail investors, as well as greater media coverage, which can have downstream consequences when taking products to market.

Overall, the findings suggest that firms exhibit peer effects in funding propensities, but a pecking order emerges in how firms respond to the increased capital of a competitor. Moreover, our findings imply that going public carries distinct advantages from other funding opportunities that may change the competitive landscape between firms. The results of this section are also consistent with those of Section 4, which indicate that firms respond to the (large) funding actions of their peers due to competitive pressures.

7 Concluding remarks

In this study, we examine whether a firm's propensity to transition to public equity markets is influenced by the recent IPO of a direct competitor. Using detailed project-level data from the biopharma industry, we develop a novel measure of competing firms based on firm project portfolio composition. This measure has the advantage of solving identification challenges common to peer effect settings. Our main results show that firm IPO propensity significantly increases after observing the IPO of a direct competitor. We find that observing a peer go public within the previous 12 months raises the propensity to undertake an IPO from a baseline rate of 0.31 percent per quarter to 0.44 percent per quarter, amounting to a 40 percent increase in IPO propensity. This result is robust to accounting for hot market effects and other common shocks that may affect competing firms' IPO decisions. Our findings contribute to our understanding of what drives a private company to go public. To the best of our knowledge, our study is the first to show that this propensity relates to the IPO decisions of competing firms narrow definition of competitors. Moreover, the analysis broadens our understanding of peer effects among *private* firms, whereas the extant literature has largely considered peer effects among public firms.

We hypothesize that the effect is driven by competitive pressures and informational spillovers. We find evidence of a competitive channel, but we find little evidence of information spillovers gleaned from peer IPOs. In additional analyses, we consider other funding decisions, such as through raising venture capital funding or being acquired, and find that peer effects operate more broadly through these other funding propensities. Two additional insights emerge from this more general analysis. First, the results highlight that the scale of the competitor's funding source matters for the peer firm's funding decision. Second, firms often utilize going public as a response to the increased capital of their peers, relative to raising VC funding or being acquired. This suggests that going public plays a distinctive role as a funding choice in overcoming competitive pressures. These general funding results are also consistent with a competitive channel driving the peer response.

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Table 1: Summary Statistics

This table contains summary statistics for all variables from 2001q1 to 2016q4. All variables are for firm i in quarter-year t. $IPO_{i,t}$ is a dummy variable, which takes a value of 100 if a private firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $LOA_{i,t-1}$ is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the firm's total number of drug-indications currently under development. $Age_{i,t-1}$ is the age of the firm in quarters. $Late\,Stage_{i,t-1}$ is the number of late-stage projects in the firm's development portfolio.

Variable	Obs	Mean	Std. Dev.	Median
$IPO_{i,t}$	74,992	0.309	5.553	0.000
$Peer\,IPO_{i,[t-4,t-1]}$	74,992	0.447	0.497	0.000
$LOA_{i,t-1}$	74,992	0.233	0.269	0.134
$Num\,Drugs_{i,t-1}$	74,992	8.877	37.811	2.000
$Age_{i,t-1}$	74,992	29.979	38.666	19.000
$Late\,Stage_{i,t-1}$	74,992	0.948	3.565	0.000

Table 2: Peer IPOs and IPO Propensity

This table provides results examining the propensity to go public based on whether a peer firm went public. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in period t, and 0 otherwise. $Peer\ IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\ Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\ Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. $S\&P\ 500\ Ret_t$ is the return on the S&P 500 index in period t. $Nasdaq\ Ret_t$ is the return on the Nasdaq index in period t. $ARCA\ Pharma\ Ret_t$ is the return on the NYSE ARCA Pharma index in period t. $ARCA\ Biotech\ Ret_t$ is the return on the NYSE ARCA Biotech index in period t. $Num\ IPO_t$ is the total number of IPOs in the biopharma sector in period t. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. Regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Peer\ IPO_{i,[t-4,t-1]}$	0.239***	0.279***	0.237***	0.196***	0.156**	0.157**	0.125**
	(0.042)	(0.047)	(0.059)	(0.059)	(0.061)	(0.062)	(0.063)
$S\&P\ 500\ Ret_{t-1}$				0.384			
				(0.643)			
$Nasdaq\ Ret_{t-1}$				0.411			
				(0.388)			
$ARCA\ Pharma\ Ret_{t-1}$				0.615			
				(0.472)			
$ARCA\ Biotech\ Ret_{t-1}$				−0.750***			
				(0.223)			
$Num\ IPO_{t-1}$				0.021***			
				(0.006)			
Avg Peer Covariates	N	N	N	N	N	N	Y
Controls	N	Y	Y	Y	N	Y	Y
Firm FEs	N	N	Y	Y	Y	Y	Y
Quarter-year FEs	N	N	N	N	Y	Y	Y
Observations	74,992	74,992	74,992	74,992	74,992	74,992	74,992
Number of Firms	2,570	2,570	2,570	2,570	2,570	2,570	2,570
R^2	0.001	0.001	0.091	0.091	0.093	0.093	0.093

Table 3: Peer IPOs and IPO Propensity, Degree of Competition

This table provides results examining the propensity to go public based on whether a peer firm went public, examining whether the effects differ based on the degree of competition that a firm faces. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $Avg\,Ind\,Concen_{i,t}$ is the mean concentration across firm i's indication categories in quarter t. In columns (1) and (2), the sample is split based on whether the firm was above- or below-median in terms of $Avg\,Ind\,Concen_{i,t-1}$. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$			
	High Competition	Low Competition	
	Low $Avg\,Ind\,Concen_{i,t-1}$	High $Avg\,Ind\,Concen_{i,t-1}$	
	(1)	(2)	(3)
$Peer\,IPO_{i,[t-4,t-1]} \times Avg\,Ind\,Concen_{i,t-1}$			−0.009*
			(0.006)
$Peer\,IPO_{i,[t-4,t-1]}$	0.205**	−0.068	0.184**
	(0.096)	(0.085)	(0.080)
$Avg\,Ind\,Concen_{i,t-1}$			0.011**
			(0.005)
Avg Peer Covariates	Y	Y	Y
Controls	Y	Y	Y
Firm FEs	Y	Y	Y
Quarter-year FEs	Y	Y	Y
Observations	37,836	37,156	74,962
R^2	0.148	0.184	0.093

Table 4: Competitive Distance from Peers

This table provides results examining the propensity to go public based on whether a peer firm went public, based on how far a firm's research portfolio strength is from a peer going public. *Distance* is defined as the average *LOA* of all of firm i's IPO peers over the previous four quarters, minus $LOA_{i,t-1}$ for firm i, in percentage points; *Distance* is set to zero if a firm does not observe a peer go public in the previous four quarters. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$,the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)
$Peer\,IPO_{i,[t-4,t-1]} \times Distance_{i,t-1}$	−0.004*	−0.004*
	(0.002)	(0.002)
$Peer\,IPO_{i,[t-4,t-1]}$	0.148**	0.115*
	(0.061)	(0.062)
$Distance_{i,t-1}$	0.002	0.139
	(0.001)	(0.146)
Avg Peer Covariates	N	Y
Controls	Y	Y
Firm FEs	Y	Y
Quarter-year FEs	Y	Y
Observations	74,992	74,992
R^2	0.093	0.093

Table 5: Outcomes for IPO Firms following Peers vs. Other IPOs

This table provides results examining IPO outcomes for firms that went public following a peer IPO compared to firms that went public not following a peer IPO. $Peer\,IPO_i^F$ is a cross-sectional variable that takes a value of 1 if a firm went public following a peer firm's IPO, and 0 if a firm went public but did not observe a peer IPO. $Delay_i$ is the number of days between the IPO filing date and IPO completion date. $Proceeds_i$ is the total proceeds amount from the IPO, in real (2016q4) dollars. $Underpricing_i$ is the first-day stock return based on the initial offer price. Controls include quarterly lags of $\log(TA)$ (in real 2016q4 dollars), $Capex$, $Cash$, $Debt$, $R\&D$, $Sales$, LOA, $Num\,Drugs$, Age, and $Late\,Stage$. Quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$\log(1+Delay)_i$	$\log(1+Proceeds)_i$	$Underpricing_i$
	(1)	(2)	(3)
$Peer\,IPO_i^F$	0.124	−0.107	0.048
	(0.123)	(0.088)	(0.080)
Controls	Y	Y	Y
Quarter-year FEs	Y	Y	Y
Observations	201	196	185
R^2	0.550	0.668	0.333

Table 6: IPO Propensity, R&D and Product Market Peers

This table provides results examining the propensity to go public based on whether a peer firm went public, using different definitions of peers. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO^{R\&D\,Peer}_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a non-approved drug project currently under development in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $Peer\,IPO^{Product\,Peer}_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has an approved drug in the same therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)	(3)
$Peer\,IPO^{R\&D\,Peer}_{i,[t-4,t-1]}$	0.212**		0.212**
	(0.085)		(0.085)
$Peer\,IPO^{Product\,Peer}_{i,[t-4,t-1]}$		0.055	0.036
		(0.067)	(0.067)
Avg Peer Covariates	Y	Y	Y
Controls	Y	Y	Y
Firm FEs	Y	Y	Y
Quarter-year FEs	Y	Y	Y
Observations	74,992	74,992	74,992
Number of Firms	2,570	2,570	2,570
R^2	0.093	0.093	0.093

Table 7: Accounting and Project Outcomes for IPO Firms following Peers vs. Other IPOs

This table provides results examining post-IPO outcomes for firms that went public following a peer IPO compared to firms that went public not following a peer IPO. The sample includes the IPO quarter and the subsequent four quarters of data for firms that went public. $Peer\,IPO_i^F$ is a cross-sectional variable that takes a value of 1 if a firm has gone public following a peer firm's IPO, and 0 if a firm has gone public but did not observe a peer IPO. $\log(TA)_{i,t}$ is the logarithm of total assets (in real 2016q4 dollars). $ROA_{i,t}$ is net income scaled by lagged total assets. $Capex_{i,t}$ is capital expenditures scaled by total assets. $Cash_{i,t}$ is cash holdings scaled by total assets. $Debt_{i,t}$ is total book debt scaled by total assets. $R\&D_{i,t}$ is R&D expenditures scaled by total assets. $Sales_{i,t}$ is total (net) sales scaled by total assets. $LOA_{i,t}$, is the average likelihood of approval for all projects in a firm's drug development portfolio in quarter t. $Num\,Drugs_{i,t}$ is the total number of drug-indications currently in the firm's development portfolio in quarter t. ROA, $Capex$, $Cash$, $Debt$, $R\&D$, and $Sales$ are winsorized at the 1% level. Controls include quarterly lags of $\log(TA)$, $Capex$, $Cash$, $Debt$, $R\&D$, $Sales$, LOA, $Num\,Drugs$, Age, and $Late\,Stage$. Quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$\log(TA)_{i,t}$	$ROA_{i,t}$	$Capex_{i,t}$	$Cash_{i,t}$	$Debt_{i,t}$	$R\&D_{i,t}$	$Sales_{i,t}$	$LOA_{i,t}$	$Num\,Drugs_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Peer\,IPO_i^F$	0.037	−0.013	0.00003	−0.001	−0.037*	−0.004	0.005	−0.005	0.051
	(0.042)	(0.027)	(0.001)	(0.010)	(0.020)	(0.006)	(0.004)	(0.004)	(0.062)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,006	1,006	1,020	1,020	1,020	1,020	1,020	1,020	1,020
Number of Firms	220	221	225	225	225	225	225	225	225
R^2	0.783	0.593	0.514	0.695	0.241	0.239	0.436	0.938	0.981

Table 8: Outcomes for IPO Firms following Peers vs. Firms that Stayed Private

This table provides results examining outcomes for firms that went public following a peer IPO compared to firms that remained private. The sample includes all private firm-years and the IPO quarter and subsequent four quarters of data for post-peer-IPO firms. $\widetilde{Peer\,IPO}_{i,t}$ is a variable that takes a value of 1 if a firm has gone public following a peer firm's IPO that occurred up through quarter $t-4$, and 0 if a firm is private in quarter t. $LOA_{i,t}$, is the average likelihood of approval for all projects in a firm's drug development portfolio in quarter t. $Num\,Drugs_{i,t}$ is the total number of drug-indications currently in the firm's drug portfolio in quarter t. $Num\,Indications_{i,t}$ is the total number of unique therapeutic indications in the firm's drug portfolio in quarter t. $Early\,Trial\,Initiation_{i,t}$ is a dummy variable that takes a value of 1 if the firm initiated a new preclinical or Phase 1 trial, and 0 otherwise. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$LOA_{i,t}$	$Num\,Drugs_{i,t}$	$Num\,Indications_{i,t}$	$Early\,Trial\,Initiation_{i,t}$
	(1)	(2)	(3)	(4)
$\widetilde{Peer\,IPO}_{i,t}$	0.001	0.161***	0.796***	0.041***
	(0.002)	(0.052)	(0.094)	(0.015)
Avg Peer Covariates	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Quarter-year FEs	Y	Y	Y	Y
Observations	75,435	75,435	75,435	75,435
Number of Firms	2,569	2,569	2,569	2,569
R^2	0.978	0.9997	0.854	0.252

Table 9: Funding Peer Effects

This table provides results examining funding propensities for private firms based on peer firm funding decisions. $VC\,Funding_{i,t}$ is a dummy variable that takes a value of 100 if the firm received venture capital funding (any or above-median, as indicated) in quarter t, and 0 otherwise. $Acquired_{i,t}$ is a dummy variable that takes a value of 100 if the firm was acquired in quarter t, and 0 otherwise. $All\,Funding_{i,t}$ is a dummy variable that takes a value of 100 if a firm either received above-median VC funding, was acquired, or did an IPO in quarter t, and 0 otherwise. $Peer\,VC_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm has received VC funding of the indicated type in the past four quarters. $Peer\,Acquired_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm was acquired in the past four quarters. $Peer\,All\,Funding_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm received above-median VC funding, was acquired, or did an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	All VC Funding	High VC Funding	Acquisition Peer Effects	All Funding Peer Effects
Dependent Variable:	$VC\,Funding_{i,t}$	$VC\,Funding_{i,t}$	$Acquired_{i,t}$	$All\,Funding_{i,t}$
$Peer\,VC_{i,[t-4,t-1]}$	0.088	0.189*		
	(0.179)	(0.108)		
$Peer\,Acquired_{i,[t-4,t-1]}$			0.101**	
			(0.049)	
$Peer\,All\,Funding_{i,[t-4,t-1]}$				0.390**
				(0.157)
Avg Peer Covariates	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Quarter-year FEs	Y	Y	Y	Y
Observations	74,760	74,760	72,008	72,486
Number of Firms	2,568	2,568	2,556	2,569
R^2	0.214	0.050	0.127	0.138

Table 10: Funding Peer Effects

This table provides results examining funding propensities for private firms based on peer firm funding decisions. $Acquired_{i,t}$ is a dummy variable that takes a value of 100 if the firm was acquired in quarter t, and 0 otherwise. $VC\,Funding_{i,t}$ is a dummy variable that takes a value of 100 if the firm received above-median venture capital funding in quarter t, and 0 otherwise. $IPO_{i,t}$ is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,VC_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm has received above-median VC funding in the past four quarters. $Peer\,Acquired_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm was acquired in the past four quarters. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$IPO_{i,t}$	$Acquired_{i,t}$	$VC\,Funding_{i,t}$	$IPO_{i,t}$	$Acquired_{i,t}$	$VC\,Funding_{i,t}$
$Peer\,VC_{i,[t-4,t-1]}$	0.204***	0.093**				
	(0.072)	(0.048)				
$Peer\,Acquired_{i,[t-4,t-1]}$			0.080	0.199***		
			(0.120)	(0.064)		
$Peer\,IPO_{i,[t-4,t-1]}$					0.080*	0.070
					(0.044)	(0.099)
Avg Peer Covariates	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Quarter-year FEs	Y	Y	Y	Y	Y	Y
Observations	74,953	75,309	74,719	74,953	75,268	74,953
Number of Firms	2,531	2,568	2,527	2,531	2,527	2,531
R^2	0.085	0.112	0.113	0.085	0.091	0.113

Appendix (For Online Publication)

A Instrumental Variables Specification

As discussed in the paper, our previous findings suggest that common shocks or other omitted variables are not driving our results. Moreover, our definition of peer groups based on a firm's particular project portfolio implies that peer groups do not perfectly coincide for peer firms in our setting, which solves the Manski (1993) reflection problem. However, to further address the possibility of unobserved common shocks or other potential endogeneity or reverse causality concerns, we use an instrumental variables (IV) approach.

We exploit the fact that, since each firm faces a potentially distinct peer group based on its own project portfolio, the set of peer groups in our data do not fully overlap. Specifically, we instrument for the IPO of a focal firm's peer by using the previous IPO decision of a firm that is a peer to the IPO-firm, but that is *not* a peer to the focal firm.[34] For example, consider three firms: A, B, and C. Suppose that firms A and B are peers because they operate in the same therapeutic category, and firms B and C are peers because they operate in the same therapeutic category, but firms A and C are not peers because they do not have any overlap in their project portfolios. In order to instrument for firm B's propensity to do an IPO—which would be $Peer\,IPO = 1$ from firm A's perspective—we would use firm C's previous IPO decision. We note that it is common for a biopharmaceutical firm to operate in disease groups that are unrelated to one another.[35]

In an IV setting with partially overlapping peer groups, the exclusion restriction is validated due to individual group shocks being uncorrelated across peer groups, but peer performance being correlated due to individual peer interactions (see, e.g., De Giorgi et al., 2010; De Giorgi, Frederiksen, and Pistaferri, 2019). In this case, it implies that firm C's IPO decision only affects firm A's IPO propensity through its (peer) effect on firm B's IPO propensity. Since firms A and C have *no* overlap in terms of their project portfolios and are thus not peers, and furthermore we control for any time-varying industry-level shocks by including quarter-year fixed effects, the exclusion restriction likely holds in our setting.

As a further validation of this, we also estimate our results when only instrumenting for

[34] De Giorgi et al. (2010) use a similar approach.

[35] As a specific example, Intercept Pharmaceuticals undertook an IPO in 2012. Intercept has a peer, Horizon Pharma, that also develops drugs in the same indication category ("Mucositis"; a condition characterized by inflammation and ulceration of the digestive tract). Horizon Pharma transitioned to public equity markets in 2011. Horizon, in turn, has a peer—Assembly Biosciences—that went public in 2010. Horizon and Assembly are peers because they both develop drugs in the indication category "Hyperparathyroidism" (over-activity of the parathyroid glands). However, Intercept and Assembly do *not* share any indication category in their project portfolios. Thus, Assembly's IPO decision would be used to instrument for Horizon's IPO, in order to estimate the propensity for Intercept to undertake an IPO.

peer IPOs using peers of peers that are *not* in the same broader ICD-10 block as the focal firm. Stated differently, we continue to define peers as firms that have drug projects within the same granular therapeutic indication category, however we include a further restriction whereby any peers of peers whose drug projects are within the same ICD-10 block(s) as the focal firm are excluded as instruments. For example, suppose firms A and B are peers due to both developing drugs in the indication category "Hyperkalemia" (a metabolic condition of elevated levels of potassium in the bloodstream). While our initial criteria would only use firm C's IPO as an instrument for firm B's IPO if firm C did not work in Hyperkalemia, our additional estimation would require firm C to also not have any projects in the broader ICD-10 block "Metabolic Disorders". Hence, all instruments are peers of peers that operate within an entirely different ICD-10 block(s) than the focal firm, which further ensures that peers of peers develop drugs in areas that are unrelated to the projects of the focal firm. In other words, this stricter criterion ensures a lack of similarity between the project portfolios of firms A and C, and thus any potential shocks experienced by the peer-of-peer firm C are unlikely to also affect the focal firm A. We note that, while therapeutic categories are sufficiently distinct from one another, this specification alleviates potential concerns of shocks that may affect any related therapeutic categories in the portfolios of firms A and C.

We estimate the following two-stage least squares (2SLS) regression. In the first stage, we instrument for $Peer\,IPO_{i,[t-4,t-1]}$ using $Peer's\,Peer\,IPO_{i,[t-8,t-5]}$, which takes a value of 1 if firm i has a peer firm that in turn has a peer (but that is not a peer to firm i) that has undertaken an IPO:[36]

$$Peer\,IPO_{i,[t-4,t-1]} = \gamma_0 + \gamma_1 Peer's\,Peer\,IPO_{i,[t-8,t-5]} + \gamma' X_{i,t-1} + \theta' Y_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \quad (3)$$

Then using instrumented $PeerIPO_{i,[t-4,t-1]}$, $\widehat{Peer\,IPO}$, we estimate the second stage:

$$IPO_{i,t} = \theta_0 + \theta_1 \widehat{Peer\,IPO}_{i,[t-4,t-1]} + \theta' X_{i,t-1} + \kappa' Y_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \quad (4)$$

As before, $X_{i,t-1}$ is a vector of control variables including $LOA_{i,t-1}$, $Num\,Drugs_{i,t-1}$, $Age_{i,t-1}$, and $Late\,Stage_{i,t-1}$. $Y_{i,t-1}$ is a vector of peer firm covariates, which include average lagged LOA, $Num\,Drugs$, Age, and $Late\,Stage$ of firm i's peer group. Finally, μ_i and η_t are firm and quarter-year fixed effects, respectively.

The results are included in Table A9. Columns (1) and (2) provide the results excluding average peer covariates, while columns (3) and (4) include average peer covariates. In the

[36] In order to be more conservative, we also exclude firm-quarters for firm i which had a direct competitor go public in the same period during which the competitor's peer went public. Our results also hold when running these regressions at a yearly frequency, instrumenting for $Peer\,IPO_{i,t-1}$ with $Peer's\,Peer\,IPO_{i,t-2}$.

first stage in columns (1) and (3), the coefficient for $Peer's\,Peer\,IPO$ is strongly positive and significant, and the F-stats are 126.12 and 106.22, respectively. This indicates that the relevance condition of the instrument is satisfied. In the second stage (columns (2) and (4)), the coefficient for $\widehat{PeerIPO}$ is positive and significant, showing that our results continue to hold even when instrumenting for a peer's IPO decision.

Columns (5) and (6) re-estimate our results while only instrumenting using the IPOs of peers of peers whose portfolios are outside any of the focal firm's ICD-10 blocks. The results are very similar when applying this stricter criterion. This suggests that the result is not driven by common shocks between potentially similar therapeutic categories. Indeed, the consistent results across all specifications provide strong support for the presence of peer effects in IPO decisions.

Overall, these results suggest that our main results are not driven by endogeneity or reverse causality stories.

Table A1: Peer IPOs, Heterogeneity by Number of Therapeutic Categories

This table provides results examining the propensity to go public based on whether a peer firm went public. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $Num\,Indications_{i,t}$ is the number of unique therapeutic indication categories that a firm has under development in quarter t. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)
$Peer\,IPO_{i,[t-4,t-1]} \times Num\,Indications_{i,t-1}$	−0.156***	−0.156***
	(0.040)	(0.041)
$Peer\,IPO_{i,[t-4,t-1]}$	0.145***	0.164***
	(0.051)	(0.057)
$Num\,Indications_{i,t-1}$	0.200***	0.200***
	(0.044)	(0.045)
Avg Peer Covariates	N	Y
Controls	Y	Y
Firm FEs	Y	Y
Quarter-year FEs	Y	Y
Observations	72,688	72,688
Number of Firms	2,531	2,531
R^2	0.004	0.004

Table A2: Peer IPOs and IPO Propensity, Sample through 2020

This table provides results examining the propensity to go public based on whether a peer firm went public, including a limited sample of firms through 2020. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in period t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. $S\&P\,500\,Ret_t$ is the return on the S&P 500 index in period t. $Nasdaq\,Ret_t$ is the return on the Nasdaq index in period t. $ARCA\,Pharma\,Ret_t$ is the return on the NYSE ARCA Pharma index in period t. $ARCA\,Biotech\,Ret_t$ is the return on the NYSE ARCA Biotech index in period t. $Num\,IPO_t$ is the total number of IPOs in the biopharma sector in period t. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2020q4. Coefficient estimates are multiplied by 100, for ease of interpretation. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Peer\,IPO_{i,[t-4,t-1]}$	0.166***	0.236***	0.258***	0.242***	0.204***	0.204***	0.193***
	(0.034)	(0.038)	(0.046)	(0.047)	(0.049)	(0.049)	(0.049)
$S\&P\,500\,Ret_{t-1}$				−0.821			
				(0.582)			
$Nasdaq\,Ret_{t-1}$				1.445***			
				(0.438)			
$ARCA\,Pharma\,Ret_{t-1}$				0.385			
				(0.379)			
$ARCA\,Biotech\,Ret_{t-1}$				−0.659***			
				(0.203)			
$Num\,IPO_{t-1}$				0.014***			
				(0.005)			
Avg Peer Covariates	N	N	N	N	N	N	Y
Controls	N	Y	Y	Y	N	Y	Y
Firm FEs	N	N	Y	Y	Y	Y	Y
Quarter-year FEs	N	N	N	N	Y	Y	Y
Observations	117,238	117,238	117,238	117,238	117,238	117,238	117,238
Number of Firms	3,848	3,848	3,848	3,848	3,848	3,848	3,848
R^2	0.0002	0.001	0.146	0.147	0.148	0.148	0.148

Table A3: Peer IPOs and IPO Propensity, Yearly Frequency

This table provides results examining the propensity to go public based on whether a peer firm went public, estimated at a yearly frequency. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t-1}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in year $t-1$. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. $S\&P\,500\,Ret_t$ is the return on the S&P 500 index in year t. $Nasdaq\,Ret_t$ is the return on the Nasdaq index in year t. $ARCA\,Pharma\,Ret_t$ is the return on the NYSE ARCA Pharma index in year t. $ARCA\,Biotech\,Ret_t$ is the return on the NYSE ARCA Biotech index in year t. $Num\,IPO_t$ is the total number of IPOs in the biopharma sector in year t. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run at the yearly level from 2001 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Peer\,IPO_{i,t-1}$	0.906***	1.243***	1.038***	0.832***	0.835***	0.833***	0.819***
	(0.143)	(0.174)	(0.208)	(0.215)	(0.222)	(0.223)	(0.224)
$S\&P\,500\,Ret_{t-1}$				−0.928			
				(1.404)			
$Nasdaq\,Ret_{t-1}$				0.584			
				(0.902)			
$ARCA\,Pharma\,Ret_{t-1}$				2.678***			
				(0.993)			
$ARCA\,Biotech\,Ret_{t-1}$				0.364			
				(0.370)			
$Num\,IPO_{t-1}$				0.024***			
				(0.006)			
Avg Peer Covariates	N	N	N	N	N	N	Y
Controls	N	Y	Y	Y	N	Y	Y
Firm FEs	N	N	Y	Y	Y	Y	Y
Year FEs	N	N	N	N	Y	Y	Y
Observations	18,467	18,467	18,467	18,467	18,467	18,467	18,467
Number of Firms	2,483	2,483	2,483	2,483	2,483	2,483	2,483
R^2	0.002	0.004	0.303	0.305	0.308	0.308	0.308

Table A4: Nonlinear Models

This table provides results examining the propensity to go public based on whether a peer firm went public, estimated using a Cox proportional hazard and probit/logit models. For the hazard model, the failure event if a firm has undertaken an IPO in a given quarter. $IPO_{i,t}$ is a dummy variable that takes a value of 1 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. The regressions are run at the quarterly level from 2001q1 to 2016q4. Hazard ratios are reported in panel A, and robust standard errors are in parentheses and clustered at the firm level. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Hazard Model

	(1)	(2)
$Peer\,IPO_{i,[t-4,t-1]}$	1.482**	1.512**
	(0.262)	(0.285)
Avg Peer Covariates	N	Y
Controls	Y	Y
Observations	74,992	74,992
Wald χ^2	28.39	42.03
Number of Firms	2,570	2,570

Panel B: Probit/Logit Model

Dependent Variable: $IPO_{i,t}$

	Probit Model		Logit Model	
	(1)	(2)	(3)	(4)
$Peer\,IPO_{i,[t-4,t-1]}$	0.237***	0.144**	0.731***	0.416**
	(0.052)	(0.062)	(0.162)	(0.190)
Avg Peer Covariates	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Quarter-year FEs	N	Y	N	Y
Observations	74,992	60,214	74,992	60,214
Number of Firms	2,570	2,568	2,570	2,568
Pseudo R^2	0.026	0.055	0.027	0.055

Table A5: Robustness: Results using Randomly Generated Peer Groups

This table provides robustness results examining the propensity to go public based on whether a peer firm went public, assigning firms to randomly generated peer groups. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO^{Placebo}_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same (randomly generated) therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)	(3)
$Peer\,IPO^{Placebo}_{i,[t-4,t-1]}$	0.069	0.058	0.040
	(0.067)	(0.067)	(0.068)
Avg Peer Covariates	N	N	Y
Controls	N	Y	Y
Firm FEs	Y	Y	Y
Quarter-year FEs	Y	Y	Y
Observations	74,992	74,992	74,992
Number of Firms	2,570	2,570	2,570
R^2	0.093	0.093	0.093

Table A6: Peer IPOs and IPO Propensity, Peer Underpricing

This table provides results examining the propensity to go public based on whether a peer firm went public, exploring whether the effect varies depending on the degree of underpricing for peers that went public. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $Peer\,Underpricing_{i,[t-4,t-1]}$ is the mean underpricing for all peer firms going public in quarters $t-1$ through $t-4$. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)	(3)
$Peer\,IPO_{i,[t-4,t-1]} \times Peer\,Underpricing_{i,[t-4,t-1]}$			0.969
			(0.975)
$Ind\,Underpricing_{i,[t-4,t-1]}$	−0.041	−0.104	−1.052
	(0.490)	(0.490)	(0.911)
$Peer\,IPO_{i,[t-4,t-1]}$		0.127**	0.125**
		(0.063)	(0.063)
Avg Peer Covariates	Y	Y	Y
Controls	Y	Y	Y
Firm FEs	Y	Y	Y
Quarter-year FEs	Y	Y	Y
Observations	74,992	74,992	74,992
Number of Firms	2,570	2,570	2,570
R^2	0.093	0.093	0.093

Table A7: Peer IPOs and IPO Propensity, Peer Stock Performance

This table provides results examining the propensity to go public based on whether a peer firm went public, exploring whether the effect varies depending on the subsequent stock returns of peers that went public. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $Peer\,Return_{i,[t-1,t-4]}$ is the mean first-quarter stock returns (measured from the IPO date to the end of that quarter) of all peer firms going public in quarters $t-1$ through $t-4$. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer characteristics include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$			
	(1)	(2)	(3)
$Peer\,IPO_{i,[t-4,t-1]} \times Peer\,Return_{i,[t-1,t-4]}$			0.013
			(0.975)
$Peer\,Return_{i,[t-1,t-4]}$	0.151	0.112	0.100
	(0.347)	(0.346)	(0.976)
$Peer\,IPO_{i,[t-4,t-1]}$		0.123**	0.123**
		(0.062)	(0.062)
Avg Peer Covariates	Y	Y	Y
Controls	Y	Y	Y
Firm FEs	Y	Y	Y
Quarter-year FEs	Y	Y	Y
Observations	74,992	74,992	74,992
R^2	0.093	0.093	0.093

Table A8: Robustness: Peer IPOs and IPO Propensity, Additional Fixed Effects

This table provides results examining the propensity to go public based on whether a peer firm went public including therapeutic indication category fixed effects. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $S\&P\,500\,Ret_t$ is the return on the S&P 500 index in quarter t. $Nasdaq\,Ret_t$ is the return on the Nasdaq index in quarter t. $ARCA\,Pharma\,Ret_t$ is the return on the NYSE ARCA Pharma index in quarter t. $ARCA\,Biotech\,Ret_t$ is the return on the NYSE ARCA Biotech index in quarter t. $Num\,IPO_t$ is the total number of IPOs in the biopharma sector in quarter t. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm, quarter-year, and therapeutic category indicators are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Observations in columns (4) and (5) exclude groups that exhibit a single degree of freedom once the fixed effects have been netted out, so as to not bias inferences (e.g., Correia, 2015).

Dependent Variable: $IPO_{i,t}$

	(1)	(2)	(3)	(4)	(5)
$Peer\,IPO_{i,[t-4,t-1]}$	0.274***	0.174***	0.231*	0.275*	0.253*
	(0.056)	(0.059)	(0.131)	(0.149)	(0.150)
$S\&P\,500\,Ret_{t-1}$		0.126			
		(0.648)			
$Nasdaq\,Ret_{t-1}$		0.751*			
		(0.392)			
$ARCA\,Pharma\,Ret_{t-1}$		0.762			
		(0.474)			
$ARCA\,Biotech\,Ret_{t-1}$		−0.845***			
		(0.224)			
$Num\,IPO_{t-1}$		0.026***			
		(0.006)			
Avg Peer Covariates	N	N	N	Y	Y
Controls	N	N	N	N	Y
Firm FEs	N	Y	Y	Y	Y
Quarter-year FEs	N	N	Y	Y	Y
Indication Category FEs	Y	Y	Y	Y	Y
ICD-10 block×Quarter-year FEs	N	N	Y	Y	Y
Observations	74,953	74,953	39,584	37,401	37,401
R^2	0.103	0.104	0.361	0.386	0.387

Table A9: Robustness: Peer IPOs and IPO Propensity, IV Specification

This table provides results examining the propensity to go public based on whether a peer firm went public, using an instrumental variable strategy. $IPO_{i,t}$ is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in quarter t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. $Peer's\,Peer\,IPO_{i,[t-8,t-5]}$ is a dummy variable, that takes a value of 1 if firm i has a peer firm that in turn has a peer (but that is not a peer to firm i) that has undertaken an IPO over the indicated time period. $\widehat{Peer\,IPO}_{i,[t-4,t-1]}$ is instrumented $Peer\,IPO_{i,[t-4,t-1]}$. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Columns (1)-(4) provide first and second stage estimates with and without average peer firm covariates, as indicated. Columns (5) and (6) only include peers of peer IPOs which are outside of the focal firm's ICD-10 blocks. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses and clustered at the firm level. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	Second stage	First stage	Second stage	First stage	Second stage
Dependent variable:	$Peer\,IPO_{i,[t-4,t-1]}$	$IPO_{i,t}$	$Peer\,IPO_{i,[t-4,t-1]}$	$IPO_{i,t}$	$Peer\,IPO_{i,[t-4,t-1]}$	$IPO_{i,t}$
$\widehat{Peer\,IPO}_{i,[t-4,t-1]}$		2.131***		2.069***		2.245***
		(0.430)		(0.416)		(0.532)
$Peer's\,Peer\,IPO_{i,[t-8,t-5]}$	0.174***		0.179***		0.149***	
	(0.008)		(0.008)		(0.008)	
Avg Peer Covariates	N	N	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Quarter-year FEs	Y	Y	Y	Y	Y	Y
Observations	48,305	48,305	48,305	48,305	35,913	35,913
Number of Firms	2,531	2,531	2,531	2,531	2,531	2,531
F-stat	126.12		106.22		100.26	

Table A10: Peer IPOs and IPO Propensity, Control Coefficients Reported

This table provides results examining the propensity to go public based on whether a peer firm went public, reporting coefficients for all variables. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 100 if the firm has undertaken an IPO in period t, and 0 otherwise. $Peer\,IPO_{i,[t-4,t-1]}$ is a dummy variable, which takes a value of 1 if a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO in the past four quarters. Controls include $LOA_{i,t-1}$, the average likelihood of approval for all projects in a firm's drug development portfolio; $Num\,Drugs_{i,t-1}$, the total number of drug-indications currently in the firm's development portfolio; $Age_{i,t-1}$, the age of the firm, presented in original units scaled by 100 to ease readability; and $Late\,Stage_{i,t-1}$, the number of late-stage projects in the firm's development portfolio. $S\&P\,500\,Ret_t$ is the return on the S&P 500 index in period t. $Nasdaq\,Ret_t$ is the return on the Nasdaq index in period t. $ARCA\,Pharma\,Ret_t$ is the return on the NYSE ARCA Pharma index in period t. $ARCA\,Biotech\,Ret_t$ is the return on the NYSE ARCA Biotech index in period t. $Num\,IPO_t$ is the total number of IPOs in the biopharma sector in period t. Average peer covariates (denoted by *Peer* in front of the respective variable names) include the lagged mean likelihood of approval, lagged mean number of drugs, lagged mean age, and lagged mean number of late stage projects across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run at the quarterly level from 2001q1 to 2016q4. Robust standard errors are in parentheses, and are clustered at the firm level. We note that the p-value for *Age* in columns (4) and (5) is 1.000 due to near-collinearity with the fixed effects. A constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: $IPO_{i,t}$

	(1)	(2)	(3)	(4)	(5)
$Peer\,IPO_{i,[t-4,t-1]}$	0.279***	0.237***	0.196***	0.157**	0.125**
	(0.047)	(0.059)	(0.059)	(0.062)	(0.063)
$S\&P\,500\,Ret_{t-1}$			0.384		
			(0.643)		
$Nasdaq\,Ret_{t-1}$			0.411		
			(0.388)		
$ARCA\,Pharma\,Ret_{t-1}$			0.615		
			(0.472)		
$ARCA\,Biotech\,Ret_{t-1}$			−0.750***		
			(0.223)		
$Num\,IPO_{t-1}$			0.021***		
			(0.006)		
$LOA_{i,t-1}$	0.048	0.467***	0.418**	0.306*	0.341**
	(0.065)	(0.171)	(0.170)	(0.166)	(0.173)
$Num\,Drugs_{i,t-1}$	0.0005	−0.002***	−0.002***	−0.003***	−0.002***
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)
$Age_{i,t-1}$	−0.000***	0.000***	0.000***	1.067	1.075
	(0.000)	(0.000)	(0.000)	(9,467)	(9,470)
$Late\,Stage_{i,t-1}$	−0.010	0.013	0.019*	0.027**	0.023**
	(0.006)	(0.010)	(0.010)	(0.011)	(0.011)
$Peer\,LOA_{i,t-1}$					0.738
					(0.599)
$Peer\,Num\,Drugs_{i,t-1}$					−0.001
					(0.003)
$Peer\,Age_{i,t-1}$					0.001
					(0.003)
$Peer\,Late\,Stage_{i,t-1}$					−0.039
					(0.026)
Firm FEs	N	Y	Y	Y	Y
Quarter-year FEs	N	N	N	Y	Y
Observations	74,992	74,992	74,992	74,992	74,992
Number of Firms	2,570	2,570	2,570	2,570	2,570
R^2	0.001	0.091	0.091	0.093	0.093