IPO Peer Effects*

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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 granular level through a novel approach based on firm project portfolios. 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. We find that this peer effect is stronger for more narrow definitions of competitors, and the effect also varies depending on the type of competitor—firms display an increased propensity of going public following an R&D competitor's IPO, but not following the IPO of a product market competitor. Furthermore, our effects are centered on firms that operate in more competitive areas. This suggests that firms which are in neck-and-neck competition to develop innovations go public shortly after their competitor in order to remain competitive. Collectively, our findings provide evidence that the IPO decisions of a firm's direct competitors significantly influences firm IPO propensity, and we identify a novel mechanism—R&D competition—by which this effect operates.

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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 their 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 their IPO plans by several quarters after observing the IPO of one of their 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.[2] Observing the IPO of a close rival may affect this tradeoff due to competitive or informational incentives. For example, the act of going public can confer competitive advantages to the newly public firm, such as attracting investor and consumer attention, providing capital to expand 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 may 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. Moreover, the underwriter's costly information acquisition regarding the evaluation of the competitor firm may be revealed during the marketing and bookbuilding process of the competitor's IPO (e.g., Benveniste et al. (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

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

[2] Theories of the choice between private and public ownership provide insight into these tradeoffs. For example, Pagano and Röell (1998) notes how public ownership may entail over-monitoring of management by external shareholders. Boot et al. (2006) analyze the private-public choice, and show that private ownership enables firms to enjoy more customized governance. Stulz (2019) argues that having a concentration of owners with specialized knowledge of the firm's business model, as is the case with private firms, may improve firm value.

in this exercise is that it requires data on private firms—both ones that go public and ones 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 statements and operating decisions are not publicly available.[3] 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 allows us to identify and construct a granular measure of each firm's direct competitors, based on the similarity of individual projects (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 624 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 reference groups at the industry level.[4] 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 simultaneity (i.e., reflection)—a major identification challenge in estimating peer effects (Manski (1993)). This allows us to distinguish the effect of a peer IPO from other covariates that may influence

[3] 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 et al. (2010)).

[4] 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.

peer behavior. Moreover, the presence of partially overlapping peers allows us to employ an instrumental variables (IV) 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 increases the probability of going public by roughly one percentage point, an increase of 57 percent compared to the baseline propensity to go public. This result holds after controlling for time and firm fixed effects, market conditions, number of IPOs, and the risk and size of the project portfolio, and also remains when accounting for other common shocks between firms.

To explore the robustness of our measure of peer firms, we consider alternative classifications based on ICD-10 Chapters and Blocks. These are both less granular classifications than our main measure, with ICD Chapter as the broadest. We find that the effect becomes *weaker* as we broaden the criteria for a competitor, and that our main measure dominates both of these when included in the same test. This provides evidence that our measure of peer firms provides explanatory power that is distinct from broader effects such as "IPO waves" that may affect a larger number of firms within the industry.

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 which 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 leads to an insignificant decrease in IPO propensity. This is consistent with theories of competition in innovation, such as Aghion et al. (2005), which predict that firm responses to competitive pressures depend on the extant nature of competition they face.[5] 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

[5]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.

the focal firm to overcome, resulting in a lower or unchanged IPO propensity.[6] These results suggest that competition in research and development plays a significant role in firms' IPO decisions. We note that the literature has largely overlooked the role of R&D competition in IPO markets, and hence identifying the salience of R&D competition in IPO decisions is an additional novel insight of our analysis.

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 may derive 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 et al. (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.

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. As previously noted, the fact that our results hold when explicitly controlling for broad market conditions and coarser measures of peer firms suggests that these concerns do not drive our findings. However, we further establish that this is the case 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 certain disease groups *by period*. Hence, this

[6]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 et al. (2014), Boot and Vladimirov (2018)).

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.

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 et al. (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).[7] Through the IV specification, we again find strongly consistent results. In the first stage, we find a strong positive relationship between a peer's competitor going public and the peer's decision to subsequently do an IPO, satisfying the relevance condition of the instrument. In the second stage, we find a positive and significant relationship between instrumented peer IPO and firm IPO propensity. 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.

Our study relates 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. This suggests that transitioning to public equity markets confers competitive advantages to newly public firms at the detriment of other firms in the industry. The contribution of the present study is that we examine specifically whether a firm's IPO propensity is related to a direct competitor recently having gone public. Moreover, our analysis is at the firm level, whereas the extant literature has largely examined competitive effects at the industry level. 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. Additionally, our granular data allows us to more finely determine a firm's direct competitors rather than focusing on overall industry

[7]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.

competition.

The present study is also related to papers which 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 showing that informational spillovers from IPOs do not seem salient among direct competitors; this 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 et al. (1998), Brau et al. (2003), Lowry (2003), Kim and Weisbach (2008), Chemmanur et al. (2010), Gao et al. (2013), and Ewens and Farre-Mensa (2019). 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)).[8] We show that peer effects are present in IPO propensity. Moreover, we examine peer effects in the decisions among *privately* held companies, while the extant literature has largely focused on public firms.[9] In addition, our granular characterization of a firm's competitors allow 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.[10] Relatedly, this study contributes to the literature which examines similarity in the sequential actions of agents in capital markets. These include herding among institutional investors (Nofsinger and Sias (1999), Sias (2004), Cai et al. (2019)), sell-side security analysts (Welch (2000), Cooper et al. (2001), Gleason and Lee (2003), Clement and Tse (2005), Keskek et al. (2014)), and firm disclosures (Brown et al. (2006), 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 we explore is an informational channel, this study relates to the literature that examines information externalities of peer disclosure and its

[8] A number of studies have also considered peer effects at the individual level, such as Kaustia and Knüpfer (2012) and Bursztyn et al. (2014).

[9] Two exceptions include Badertscher et al. (2013) and Shroff et al. (2017), which consider the variation in investment and cost of debt capital for private firms among industries with greater public firm disclosure.

[10] A few papers 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.

effects on firm characteristics and decisions. These studies have found that greater peer disclosure influences firm share price (Foster (1981), Baginski (1987), Han et al. (1989)), liquidity (Bushee and Leuz (2005)), investment (Badertscher et al. (2013), Chen et al. (2013), Shroff et al. (2014)), and cost of capital (Shroff et al. (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 (Gleason et al. (2008), Beatty et al. (2013), Li (2016)), 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 increases. 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 costs of similar firms.

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 is a potential advantage from going public that is

particularly salient among *R&D competitors*. Consistent with the notion of an advantage through a decrease in the debt-to-equity ratio, Hsu et al. (2010) find that highly leveraged public firms are more adversely affected by new IPOs within their industry. Chevalier (1995), Phillips (1995), Zingales (1998), and Campello (2003, 2006) similarly find that high debt levels are negatively associated with performance.

Second, the bookbuilding and marketing process of the IPO allows the issuing firm to help gain the attention of institutional investors. This may be useful in later periods if the firm seeks external finance through equity private placements. Relatedly, 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 et al. (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.

The IPO can confer additional competitive advantages to firms in other, less direct ways as well. 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 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 et al. (2003), Dittmar and Mahrt-Smith (2007), among others). 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 equity markets can also be costly. For example, going public may exacerbate agency frictions among management and strengthen short termism (e.g., Stein (1989)). Relatedly, public firms are subject to greater public disclosure requirements, increasing a firm's proprietary disclosure costs (Guo et al. (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.

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 of a close peer when determining the price range of its IPO, thereby saving themselves the research and information gathering costs.[11] Likewise, an underwriter who 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 themselves, as they can save on costly information gathering and due diligence.[12]

Relatedly, informational spillovers from a competitor's IPO may be present in other forms. In particular, 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)). 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

[11]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).

[12]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.

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 may 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.

Both of 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.

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. from 2000 to 2016. 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, and the therapeutic indication category that the drug falls into. The database 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.

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 yields a sample of 2,021 private firms with 14,645 firm-year observations, and a total of 229 IPOs in our sample. We also obtain additional balance sheet information from Compustat, 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, in cases where these data are missing in SDC Platinum.

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 an active drug project in development that is in the same granular therapeutic indication category as an actively developed drug project in firm i's project portfolio. There are 624 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 example, 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). However, we also explore how our results are affected by broader definitions of peers.

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.[13] Specifically, 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

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

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 et al. (2009) and De Giorgi et al. (2010), the use of partially overlapping peer groups, or peer group heterogeneity, completely solves the reflection problem.[14] 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 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-year level:[15]

$$IPO_{i,t} = \beta_0 + \beta_1 Peer\, IPO_{i,t-1} + \beta_2 LOA_{i,t-1} + \beta_3 Num\, Drugs_{i,t-1} + \theta' Y_{i,t-1} + \gamma' X_{t-1} + \mu_i + \eta_t + \varepsilon_{i,t}, \tag{1}$$

In equation (1), $IPO_{i,t}$ is a dummy variable which takes a value of one if firm i has undertaken an IPO in year t, and zero if it remains private in year t. A firm is removed from our sample once it has gone public. $Peer\, IPO_{i,t-1}$ 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 year, and zero otherwise. $Peer\, IPO_{i,t-1}$ 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. $LOA_{i,t-1}$ is the mean (lagged) likelihood of eventual approval of firm i's drug projects, which controls for the risk

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

[15] For robustness, we demonstrate that our results hold when we run our main tests using a hazard specification, and at the firm-quarter level.

of a firm's project development portfolio. $Num\,Drugs_{i,t-1}$ is the total (lagged) number of drugs in firm i's project portfolio, as a measure of firm size. Y_{t-1} represents a vector of mean peer firm covariates, which include average lagged LOA and $Num\,Drugs$ of firm i's peer group; including these allow us to condition on the action of a firm's peer group (IPO) while controlling for the characteristics of the peer group. X_{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 as well as the total number of IPOs in the biopharma sector for that period. Finally, μ_i and η_t are firm and year fixed effects, respectively. With the inclusion of firm and year fixed effects, the interpretation of equation (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.

We note that 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 as control variables in another specification that does not include time fixed effects (when time fixed effects are included, these variables are completely subsumed). This 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 0.014, indicating that the overall sample propensity to do an IPO for a firm in a given year is 1.4 percent. $Peer\,IPO_{i,t}$ has a mean of 0.422 but a median of 0.000, which suggests that while the majority of firms do not observe a peer going IPO in a given year, a substantial number 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 25 percent, indicating that the average firm has a mean drug approval likelihood of 25 percent. Finally, a given firm has a mean of roughly 5 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.

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)). 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 year as controls. Column (5) adds firm and 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 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 $Peer\,IPO_{i,t-1}$ are positive and significant at the 1 percent level.[16] In particular, the magnitude indicates that firms which observe a peer firm go public are roughly 0.8 to 1 percent more likely to go public themselves relative to other firms. Given a baseline IPO rate of 1.4 percent at the firm-year level (as shown in the summary statistics), this suggests that observing a peer going public increases a given firm's IPO propensity in a given year by roughly 57 percent relative to the population of private biopharma firms. Put differently, this represents a roughly 90 percent increase in IPO propensity when compared to the baseline IPO rate at the firm-year level for firms that do not observe the recent IPO of a direct competitor. This provides 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.[17]

We next explore the timing of the peer IPO effect. In Table 3, we examine whether

[16] 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 Appendix Table A2 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 follower the IPO of a direct competitor. 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.

[17] An alternative definition of our main variable would be to examine the proportion of a firm's drug portfolio for which a peer firm has undertaken an IPO. For example, if a firm has two projects and a peer firm for one of them goes public, we would expect the effect to be stronger than for another firm which has five projects and a peer firm for one them goes public. In Appendix Table A3, we re-run our main specification using a continuous treatment variable which measures the proportion of the indication categories in firm i's drug portfolio for which a peer firm has gone public, rather than a discrete measure. We find very similar results using this alternative measure. Along similar lines, we also run a specification, Appendix Table A1, where we interact our main explanatory variable $Peer\,IPO_{i,t-1}$ 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 the effect being stronger if a firm has fewer peers. Finally, our results do not seem to be driven by strategic concerns related to venture capital ownership. In particular, in supplemental tests explicitly controlling for ownership by each individual VC firm in our sample, we still find the same results.

observing a peer firm undertake an IPO two or three years prior has any predictive power for a firm's decision to go public. We find that only observing a peer go public in the prior year has any significant effect on IPO propensity—observing a peer IPO further back in time does not have a significant effect. This suggests that the peer IPO effect is relatively immediate; firms do not wait long after seeing a peer go public in order to make the decision themselves.[18]

4.2 Definition of Peers

Granularity of Peer Definition

In our main tests, we define a peer firm narrowly as one that has a drug in the same therapeutic area as a drug in the focal firm's project portfolio. While this provides us a more granular identification of peer firms, it is informative to empirically examine whether this definition of peer firms actually gives us additional explanatory power in terms of identifying peer IPO effects. This can also inform us as to whether the effects that we find are driven by specific peer effects, or broader effects akin to "IPO waves" that affect a larger number of firms within the industry.

In order to explore this, we re-run our main test using two broader definitions of peers. We utilize the ICD-10 classification system for diseases, which provides a hierarchy for diagnosing diseases that is used by medical professionals. The ICD-10 classification system for our sample includes 21 broad disease group Chapters and 161 Blocks within those Chapters. An example of an ICD-10 Chapter would be "diseases of the respiratory system" (Chapter 10), while an example of a Block within that Chapter would be "acute upper respiratory infections" (Block J00-J06). We assign each drug in our sample to an ICD-10 Chapter and Block based on the disease that it targets, and use these classifications to re-define peer firms. This allows us to create two new variables that indicate whether a peer firm has gone public—$Peer\,IPO_{i,t-1}^{ICD\,Chapter}$ and $Peer\,IPO_{i,t-1}^{ICD\,Block}$—that utilize the definition of peers based on ICD-10 Chapters and ICD-10 Blocks, respectively. (We drop subscripts in the ensuing discussion for ease of readability.)

[18] Our main tests are run at the firm-year level, and explore whether seeing a peer firm go public in the previous year significantly influences the probability of a focal firm going public in the current year. This allows us to account for the time it takes to go through the IPO process after seeing a peer do so. As an alternative measure, we define a peer IPO as a firm whose direct competitor went public in the previous 12 months. In Table A4 in the Appendix, we run our main test at the quarterly level, and define our peer IPO variable—$Peer\,IPO_{i,[t-4,t-1]}$—as taking a value of 1 if a peer firm has undertaken an IPO in the past four quarters. Our results still strongly hold even when defining our peer IPO variable more flexibly and using quarterly data.

Table 4 provides the results using these alternative definitions. Column (1) shows that $Peer\,IPO^{ICD\,Chapter}$ is insignificant. This suggests that examining peer IPOs using the broadest definition of peers does not yield any additional explanatory power—put differently, such a broad definition of peers includes a large number of firms within the industry, and the broad IPO activity of the industry is accounted for by year fixed effects. In column (2), $Peer\,IPO^{ICD\,Block}$ is positive and significant. This shows that increasing the granularity of the definition of peers provides additional explanatory power, over and above broader trends for the industry. Column (3) replicates the results from Table 1 column (6) for comparison, and shows that relative to the coarser definition of peers used in $Peer\,IPO^{ICD\,Block}$, using the narrowly defined indication categories increases both the point estimate and significance of the effect. Finally, column (4) includes all three versions of the peer IPO variable, and shows that only $Peer\,IPO_{i,t-1}$ when defined by the 624 therapeutic indication categories is significant. This provides evidence that the most narrow definition of peer firms indeed provides additional identifying power in our tests, and suggests that the effects that we show in our main tests are likely not due to broader trends affecting broader disease groups.[19]

R&D and Product Market Peers

Beyond the granularity of the definition of a firm's direct competitors or peers that we use, we also 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. In our main tests, we do not distinguish between approved drugs and drugs in development, and thus we combine both types of peers in defining our main variable. Here, we explore whether the distinction between these two types of peers matters.

To examine this, we split our main variable, $Peer\,IPO_{i,t-1}$, into R&D competitors, $Peer\,IPO_{i,t-1}^{R\&D\,Peer}$, and product market competitors, $Peer\,IPO_{i,t-1}^{Product\,Peer}$. (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

[19]We provide further evidence of this in subsequent robustness tests.

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 5 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 negative and 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, and may even be *less* likely to do so. Column (3) includes both measures in the same regression, and confirms that these results continue to hold.

The results in Table 5 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 matter. 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 or reversed if firms perceive that the leader is too far out of reach.

These results also provide novel insights into the role of competition in IPO propensity. The findings suggest that R&D competition and peer behavior plays a significant role in a firm's propensity to go public. This provides a novel addition to the existing IPO literature which has largely focused on product market considerations.

4.3 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 so as to not miss out on the competitive advantages inherent in going public, such as 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 rents that lower the cost of going public (Benveniste et al. (2002)) or signal positive information about the firm's prospects.

In this section, we further explore the competitive channel. At a basic level, if firms are making their decisions to go IPO 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 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 to a small number of firms, this implies that the category is *less* competitive.[20] Then, for each firm i in each year t, we create $Avg\,Ind\,Concen_{i,t-1}$ as the mean concentration across firm i's drug indication categories.

Table 6 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 $Avg\,Ind\,Concen$ (higher levels of competition).

Overall, the results suggest that our main effects are centered on firms that face the greatest degree of competition, which is consistent with competitive effects being an important mechanism through which peer effects in IPOs operate.

4.4 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

[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.

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 who 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 immediately 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 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 IPO 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 is 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 7. 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 Table 8 and are not significant. Overall, the results provide little support that potential 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

[21]These variables come from SDC Platinum. Underpricing is defined as the first day's trading return relative to the IPO offer price.

eliminates any information spillovers regarding sentiment or information production that are shared at the industry level.

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 9, we test ex post performance by restricting our sample to the first three years of data for firms that have gone public, and examining a variety of accounting, project, and IPO outcomes.[22] As in Section 4.4, 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, and 0 if a firm has gone public but did not observe a peer IPO.

In Table 9, we examine the effect for a number of accounting variables: size (total assets), profitability (return on assets, ROA, measured via EBIT), capital expenditures (capex), cash holdings, debt, R&D expenditures, and sales.[23] We also explore LOA and $Num\,Drugs$ to examine whether there are any significant changes in firms' project portfolio characteristics.[24] Across all accounting variables (with the exception of capex, 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 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

[22] The results are qualitatively similar for longer time windows.

[23] All accounting outcomes, with the exception of total assets, are scaled by total assets and are winsorized at the 1% level.

[24] 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 all of the dependent variables as controls in each of the regressions.

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 $\widetilde{PeerIPO}_{i,t-1}$ at the firm-year level that takes a value of 1 if a firm has gone public following a peer firm's IPO between years $t-1$ and $t-3$, and 0 if a firm stays private in year t after observing a peer go IPO.[25] 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 I trial testing.

Table 10 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 exhibit an increase in their portfolio likelihood of approval (a decrease in portfolio risk), 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.

4.6 Robustness: 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, 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 624 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 differences across indication

[25] We define this variable to switch on for three years to be consistent with the tests in in 7, and in order to account for the possibility that changes in firms' project portfolios may manifest themselves only after a delay.

categories in the propensity to go public. We additionally add ICD chapter-by-year or ICD block-by-year fixed effects, which control for shocks in any particular year that are common to firms working in a given area.[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 11. As shown in the table, even when including each of these fixed effects, $Peer\,IPO_{i,t-1}$ 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.

5 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.

5.1 Methodology

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

[26] 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 block-by-year level.

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

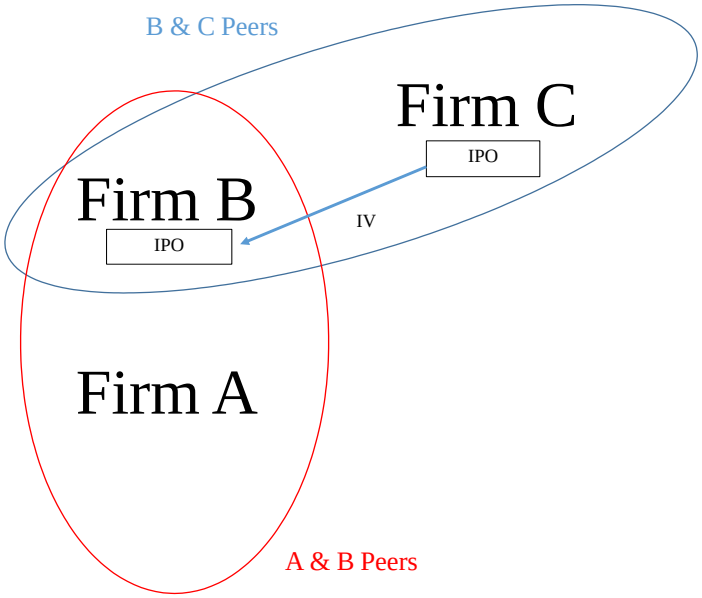

Figure 1: Graphical representation of the instrumental variables strategy.

previous IPO decision. Figure 1 graphically depicts this strategy.

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" (overactivity 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. Moreover, as illustrated by this example, it is common for a firm to operate in disease groups that are unrelated to one another.

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 et al. (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 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 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 who 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 who 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 $Peer\,IPO_{i,t-1}$ using $Peer's\,Peer\,IPO_{i,t-2}$, 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:[28]

$$Peer\,IPO_{i,t-1} = \gamma_0 + \gamma_1 Peer's\,Peer\,IPO_{i,t-2} + \gamma_2 LOA_{i,t-1} + \gamma_3 Num\,Drugs_{i,t-1} + \theta' Y_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \tag{2}$$

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

$$IPO_{i,t} = \theta_0 + \theta_1 \widehat{Peer\,IPO}_{i,t-1} + \theta_2 LOA_{i,t-1} + \theta_3 Num\,Drugs_{i,t-1} + \kappa' Y_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \tag{3}$$

As before, $LOA_{i,t-1}$ is the mean (lagged) likelihood of eventual approval of firm i's drug projects, and $Num\,Drugs_{i,t-1}$ is the total (lagged) number of drugs in firm i's project portfolio. Y_{t-1} is a vector of mean peer firm covariates, which include average lagged LOA and $Num\,Drugs$ of firm i's peer group. Finally, μ_i and η_t are firm and year fixed effects,

[28] In order to be more conservative, we also exclude firm-years for firm i which had a direct competitor go public in year $t-2$.

respectively.

5.2 Results

The results are included in Table 12. Columns (1) and (2) provide the results excluding average peer covariates, while columns (3) and (4) include average peer covariates. In the first stage in columns (1) and (3), the coefficient for $Peer's\, Peer\, IPO$ is strongly positive and significant, and the F-stats are 43.61 and 44.62, 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 Blocks. The results are very similar when applying this stricter criterion, with a point estimate and significance in the second stage that is nearly identical to that in column (4). 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.

6 Concluding remarks

In this study, we examine whether a firm's IPO propensity is influenced by the recent IPOs of their direct competitors. Using detailed project-level data to identify direct competitors, we find that firm IPO propensity significantly increases after observing the IPO of a direct competitor. This main result contributes 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.

We hypothesize that the effect is driven by competitive pressures and informational spillovers. We further decompose our measure of a firm's competitors into product market and R&D competitors. These analyses reveal that the increase in IPO propensity for rival firms is partly driven by R&D competition, which also indicates that R&D competition plays a significant role in the going-public decision among competing firms. This provides an additional insight of our analysis in that we document the salience of R&D competition

in IPO decisions. In contrast to the competitive channel, our results provide little support for informational externalities contributing to the increase in IPO propensity following competing firms.

Finally, we develop a novel measure of competing firms based on project portfolio composition. This measure provides explanatory power above broader criteria for competing firms. Moreover, we control for hot market effects and other common shocks that may affect competing firms' IPO decisions. We provide additional validity for our results through an instrumental variables approach. Taken together, this analysis provides strong support for the hypothesis that firms respond to the IPO decisions of their direct competitors by increasing their own propensity to go public.

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Table 1: Summary Statistics

This table contains summary statistics for all variables from 2000 to 2016. $IPO_{i,t}$ is a dummy variable, which takes a value of 1 if a private firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $LOA_{i,t}$ is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t}$ is the firm's total number of drug-indications currently under development.

Variable	Obs	Mean	Std. Dev.	Median
$IPO_{i,t}$	16,907	0.014	0.116	0.000
$Peer\,IPO_{i,t}$	16,678	0.422	0.494	0.000
$LOA_{i,t}$	16,907	0.251	0.191	0.194
$Num\,Drugs_{i,t}$	16,907	5.192	17.183	2.000

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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently 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 and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 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)
$Peer\,IPO_{i,t-1}$	0.010***	0.011***	0.018***	0.010***	0.008***	0.008***	0.009***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$LOA_{i,t-1}$		0.001	0.025**	0.021**		0.021**	0.027**
		(0.005)	(0.010)	(0.010)		(0.010)	(0.012)
$Num\,Drugs_{i,t-1}$		−0.0001***	0.0001**	−0.00002		−0.00005	−0.00003
		(0.00002)	(0.00005)	(0.00004)		(0.00004)	(0.00004)
$S\&P\,500\,Ret_{t-1}$				−0.026			
				(0.018)			
$Nasdaq\,Ret_{t-1}$				0.017			
				(0.011)			
$ARCA\,Pharma\,Ret_{t-1}$				0.049***			
				(0.013)			
$ARCA\,Biotech\,Ret_{t-1}$				0.003			
				(0.005)			
$Num\,IPO_{t-1}$				0.0003***			
				(0.0001)			
Avg Peer Covariates	N	N	N	N	N	N	Y
Firm FEs	N	N	Y	Y	Y	Y	Y
Year FEs	N	N	N	N	Y	Y	Y
Observations	14,645	14,645	14,645	14,645	14,645	14,645	14,492
Number of Firms	2,021	2,021	2,021	2,021	2,021	2,021	2,013
R^2	0.002	0.002	0.300	0.305	0.308	0.308	0.316

Table 3: Peer IPOs and IPO Propensity, Timing of Effect

This table provides results examining the propensity to go public based on whether a peer firm went public, exploring differential timing for the effects. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,t-1}$	0.009***			0.008**
	(0.003)			(0.003)
$Peer\,IPO_{i,t-2}$		−0.001		−0.003
		(0.003)		(0.004)
$Peer\,IPO_{i,t-3}$			−0.001	0.0001
			(0.003)	(0.003)
$LOA_{i,t-1}$	0.027**	0.025*	0.021	0.021
	(0.012)	(0.014)	(0.015)	(0.015)
$Num\,Drugs_{i,t-1}$	−0.00003	−0.00003	−0.00004	−0.00005
	(0.00004)	(0.00005)	(0.0001)	(0.0001)
Avg Peer Covariates	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Observations	14,492	12,450	10,619	10,578
Number of Firms	2,013	1,850	1,688	1,6986
R^2	0.316	0.339	0.407	0.409

Table 4: Peer IPOs and IPO Propensity, Peer Definition

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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $Peer\,IPO_{i,t}^{ICD\,Block}$ 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 ICD-10 Block, has undertaken an IPO. $Peer\,IPO_{i,t}^{ICD\,Chapter}$ 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 ICD-10 Chapter, has undertaken an IPO. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,t-1}^{ICD\,Chapter}$	0.004			0.002
	(0.003)			(0.003)
$Peer\,IPO_{i,t-1}^{ICD\,Block}$		0.006**		0.0003
		(0.003)		(0.003)
$Peer\,IPO_{i,t-1}$			0.009***	0.008**
			(0.003)	(0.004)
$LOA_{i,t-1}$	0.023*	0.021*	0.027**	0.021*
	(0.012)	(0.012)	(0.012)	(0.012)
$Num\,Drugs_{i,t-1}$	−0.00006***	−0.00006	−0.00003	−0.0001***
	(0.00002)	(0.00002)	(0.00004)	(0.00002)
Avg Peer Covariates	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Observations	14,316	14,040	14,492	14,040
Number of Firms	2,003	1,973	2,013	1,973
R^2	0.317	0.323	0.316	0.323

Table 5: 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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t-1}^{R\&D\,Peer}$ 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. $Peer\,IPO_{i,t-1}^{Product\,Peer}$ 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. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. $Num\,IPO_t$ is the total number of IPOs in the biopharma sector in year t. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,t-1}^{R\&D\,Peer}$	0.009***		0.009***
	(0.003)		(0.003)
$Peer\,IPO_{i,t-1}^{Product\,Peer}$		−0.004	−0.004
		(0.005)	(0.005)
$LOA_{i,t-1}$	0.025**	0.021**	0.024**
	(0.010)	(0.010)	(0.010)
$Num\,Drugs_{i,t-1}$	−0.0001	−0.00003	−0.00004
	(0.00004)	(0.00005)	(0.00005)
Avg Peer Covariates	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Observations	14,063	14,484	14,063
Number of Firms	2,010	2,013	2,010
R^2	0.318	0.315	0.318

Table 6: 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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $Avg\,Ind\,concen_{i,t}$ is the mean concentration across firm i's indication categories in year 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, and $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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 $Avg\,Ind\,Concen_{i,t-1}$	Low Competition High $Avg\,Ind\,Concen_{i,t-1}$	
	(1)	(2)	(3)
$Peer\,IPO_{i,t-1} \times Avg\,Ind\,Concen_{i,t-1}$			−0.031***
			(0.012)
$Peer\,IPO_{i,t-1}$	0.013***	0.003	0.029**
	(0.004)	(0.004)	(0.012)
$Avg\,Ind\,Concen_{i,t-1}$			−0.0004
			(0.007)
$LOA_{i,t-1}$	0.041*	0.019	0.029**
	(0.021)	(0.016)	(0.012)
$Num\,Drugs_{i,t-1}$	0.0002	−0.0001	−0.00004
	(0.0003)	(0.00005)	(0.00004)
Avg Peer Covariates	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Observations	7,449	7,043	14,417
Number of Firms	1,596	1,417	2,013
R^2	0.393	0.435	0.312

Table 7: 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. The sample includes the first three years of data for all public biopharma firms after their IPO. $PeerIPO_i^F$ 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. $Proceeds_i$ is the total proceeds amount from the IPO. $Underpricing_i$ is the first-day stock return based on the initial offer price. Lags of $\log(TA)$, ROA, $Capex$, $Cash$, $Debt$, $R\&D$, $Sales$, LOA, and $Num\,Drugs$ are included as controls, and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses. 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)
$PeerIPO_i^F$	−0.189	0.035	−0.035
	(0.145)	(0.096)	(0.052)
Controls	Y	Y	Y
Year FEs	Y	Y	Y
Observations	101	173	167
R^2	0.558	0.355	0.189

Table 8: Peer IPOs and IPO Propensity, Indication Category 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 in the indication category. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $Ind\,Underpricing_{i,t}$ is the mean underpricing for all peer firms going IPO in year t. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,t-1} \times Ind\,Underpricing_{i,t-1}$			−0.004
			(0.010)
$Ind\,Underpricing_{i,t-1}$	−0.00006	−0.0003	0.0004
	(0.003)	(0.003)	(0.003)
$Peer\,IPO_{i,t-1}$		0.009***	0.009***
		(0.003)	(0.004)
$LOA_{i,t-1}$	0.027**	0.027**	0.027**
	(0.011)	(0.012)	(0.012)
$Num\,Drugs_{i,t-1}$	−0.00003	−0.00003	−0.00004
	(0.00004)	(0.00004)	(0.00004)
Avg Peer Covariates	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Observations	14,492	14,492	14,492
Number of Firms	2,013	2,013	2,013
R^2	0.315	0.316	0.316

Table 9: 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 first three years of data for all public biopharma firms after their IPO. $PeerIPO_i^F$ 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. $ROA_{i,t}$ is earnings before interest, taxes, and depreciation scaled by 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 year t. $Num\,Drugs_{i,t}$ is the total number of drug-indications currently in the firm's development portfolio in year t. *ROA*, *Capex*, *Cash*, *Debt*, *R&D*, and *Sales* are winsorized at the 1% level. Lags of each of these variables are included as controls, and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO\,Public_i$	0.027	0.042	0.004*	0.020	0.007	−0.040	0.017	−0.013	0.184
	(0.074)	(0.045)	(0.002)	(0.016)	(0.026)	(0.032)	(0.021)	(0.010)	(0.114)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	481	481	481	481	478	481	481	488	488
Number of Firms	187	187	187	187	185	187	187	189	189
R^2	0.566	0.158	0.268	0.565	0.099	0.144	0.315	0.707	0.860

Table 10: 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 first three years of data for post-peer-IPO firms. $\widetilde{Peer\,IPO}_{i,t-1}$ is a variable that takes a value of 1 if a firm has gone public following a peer firm's IPO between years $t-1$ and $t-3$, and 0 if a firm is private in year t. $LOA_{i,t}$, is the average likelihood of approval for all projects in a firm's drug development portfolio in year t. $Num\,Drugs_{i,t}$ is the total number of drug-indications currently in the firm's drug portfolio in year t. $Num\,Indications_{i,t}$ is the total number of unique therapeutic indications in the firm's drug portfolio in year t. $Early\,Trial\,Initiations_{i,t}$ is the number of initiations of new pre-clinical or Phase I trials. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. Constant term is included in all regressions, but not reported. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$LOA_{i,t}$	$Num\,Drugs_{i,t}$	$Num\,Indications_{i,t}$	$Early\,Trial\,Initiations_{i,t}$
	(1)	(2)	(3)	(4)
$\widetilde{Peer\,IPO}_{i,t-1}$	0.012*	0.338*	0.802***	0.367*
	(0.007)	(0.185)	(0.260)	(0.200)
$LOA_{i,t-1}$	0.612***	−0.206	−0.280	−0.357***
	(0.016)	(0.177)	(0.384)	(0.126)
$Num\,Drugs_{i,t-1}$	0.00002	0.915***	0.636***	0.194***
	(0.0001)	(0.012)	(0.025)	(0.009)
Avg Peer Covariates	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Observations	14,597	14,597	14,544	14,597
Number of Firms	2,003	2,003	1,997	2,003
R^2	0.872	0.991	0.966	0.847

Table 11: 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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently 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. verage peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm, year, and lagged therapeutic indication category fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,t-1}$	0.009***	0.008***	0.008***	0.007**	0.017**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)
$LOA_{i,t-1}$	0.044***		0.031***	0.041***	0.040*
	(0.013)		(0.012)	(0.014)	(0.021)
$Num\,Drugs_{i,t-1}$	−0.002**		−0.002**	−0.0004	0.020**
	(0.001)		(0.001)	(0.001)	(0.010)
$S\&P\,500\,Ret_{t-1}$	−0.011				
	(0.019)				
$Nasdaq\,Ret_{t-1}$	0.004				
	(0.013)				
$ARCA\,Pharma\,Ret_{t-1}$	0.048***				
	(0.015)				
$ARCA\,Biotech\,Ret_{t-1}$	0.004				
	(0.005)				
$Num\,IPO_{t-1}$	0.0003***				
	(0.0001)				
Avg Peer Covariates	Y	N	N	Y	Y
Firm FEs	Y	Y	Y	N	Y
Year FEs	N	Y	Y	Y	Y
Indication Category FEs	Y	Y	Y	Y	Y
ICD Chapter×Year FEs	N	N	N	Y	N
ICD Block×Year FEs	N	N	N	N	Y
Observations	14,349	14,498	14,498	14,075	7,375
R^2	0.357	0.351	0.352	0.381	0.496

Table 12: 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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $Peer's\,Peer\,IPO_{i,t}$ is a dummy variable, 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. $\widehat{Peer\,IPO}_{i,t}$ is instrumented $Peer\,IPO_{i,t}$. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs 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 Blocks. The regressions are run from 2000 to 2016. 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:	$Peer\,IPO_{i,t-1}$	$IPO_{i,t}$	$Peer\,IPO_{i,t-1}$	$IPO_{i,t}$	$Peer\,IPO_{i,t-1}$	$IPO_{i,t}$
$\widehat{Peer\,IPO}_{i,t-1}$		0.192***		0.179***		0.179***
		(0.046)		(0.044)		(0.059)
$Peer's\,Peer\,IPO_{i,t-2}$	0.055***		0.058***		0.048***	
	(0.012)		(0.012)		(0.013)	
$LOA_{i,t-1}$	−0.138***	0.041***	−0.102**	0.036**	−0.108**	0.039**
	(0.044)	(0.014)	(0.048)	(0.014)	(0.051)	(0.015)
$Num\,Drugs_{i,t-1}$	0.016***	−0.002**	0.014***	−0.002**	0.019***	−0.002
	(0.004)	(0.001)	(0.004)	(0.0007)	(0.003)	(0.001)
Avg Peer Covariates	N	N	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Observations	9,304	9,304	9,293	9,293	7,428	7,428
Number of Firms	1,685	1,685	1,681	1,681	1,565	1,565
F-stat	43.61		44.62		30.00	

Appendix (For Online Publication)

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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Peer\,IPO_{i,t}$ 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. $Num\,Indications_{i,t}$ is the number of unique therapeutic indication categories that a firm has under development in year t. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)	
$Peer\,IPO_{i,t-1} \times Num\,Indications_{i,t-1}$	−0.001***	−0.001***	−0.002***	−0.001***
	(0.0002)	(0.0002)	(0.0004)	(0.0003)
$Peer\,IPO_{i,t-1}$	0.014***	0.010***	0.013***	0.013***
	(0.002)	(0.003)	(0.003)	(0.003)
$Num\,Indications_{i,t-1}$	−0.0005*	−0.0001	0.003***	0.003***
	(0.0003)	(0.0003)	(0.0007)	(0.001)
$LOA_{i,t-1}$	0.002	0.004	0.022**	0.028**
	(0.005)	(0.005)	(0.010)	(0.012)
$Num\,Drugs_{i,t-1}$	0.0004***	0.0003**	−0.0004**	−0.0004**
	(0.0001)	(0.001)	(0.0002)	(0.0002)
Avg Peer Covariates	N	N	N	Y
Firm FEs	N	N	Y	Y
Year FEs	N	Y	Y	Y
Observations	14,645	14,645	14,645	14,492
Number of Firms	2,021	2,021	2,021	2,013
R^2	0.003	0.010	0.309	0.317

Table A2: Robustness: Peer IPOs and IPO Propensity, Hazard Specification

This table provides results examining the propensity to go public based on whether a peer firm went public, estimated using a Cox proportional hazard model. The failure event if a firm has undertaken an IPO in a given year. $Peer\,IPO_{i,t}$ 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. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. The regressions are run from 2000 to 2016. Hazard ratios are reported, and 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)
$Peer\,IPO_{i,t-1}$	1.409**	1.700***	1.855***
	(0.233)	(0.304)	(0.346)
$LOA_{i,t-1}$		1.395	1.298
		(0.514)	(0.569)
$Num\,Drugs_{i,t-1}$		0.972***	0.977***
		(0.009)	(0.007)
Avg Peer Covariates	N	N	Y
Observations	16,080	14,645	14,492
Wald χ^2	4.29	14.14	18.44
Number of Firms	2,137	2,021	2,013

Table A3: Robustness: Peer IPOs as a Proportion of Firm's Indication Categories

This table provides robustness results examining the propensity to go public based on whether a peer firm went public, using an alternative definition of peer IPOs. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Prop\,Peer\,IPO_{i,t}$ is a continuous variable, which measures the proportion of the indication categories in firm i's drug portfolio for which a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently 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 and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Prop\,Peer\,IPO_{i,t-1}$	0.014***	0.015***	0.023***	0.011***	0.008**	0.009**	0.009**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$LOA_{i,t-1}$		0.002	0.022**	0.019*		0.020**	0.027**
		(0.005)	(0.010)	(0.010)		(0.010)	(0.011)
$Num\,Drugs_{i,t-1}$		−0.0001***	0.0002***	0.0001		−0.00003	−0.00002
		(0.00001)	(0.0001)	(0.00005)		(0.00004)	(0.00005)
$S\&P\,500\,Ret_{t-1}$				−0.023			
				(0.018)			
$Nasdaq\,Ret_{t-1}$				0.015			
				(0.011)			
$ARCA\,Pharma\,Ret_{t-1}$				0.049***			
				(0.013)			
$ARCA\,Biotech\,Ret_{t-1}$				0.001			
				(0.005)			
$Num\,IPO_{t-1}$				0.0003***			
				(0.0001)			
Avg Peer Covariates	N	N	N	N	N	N	Y
Firm FEs	N	N	Y	Y	Y	Y	Y
Year FEs	N	N	N	N	Y	Y	Y
Observations	14,645	14,645	14,645	14,6745	14,645	14,645	14,492
Number of Firms	2,021	2,021	2,021	2,021	2,021	2,021	2,013
R^2	0.002	0.002	0.299	0.305	0.308	0.308	0.315

Table A4: Robustness: Peer IPOs and IPO Propensity, Quarterly Data

This table provides results examining the timing of the propensity to go public based on whether a peer firm went public, run at the firm-quarter level. The dependent variable is $IPO_{i,t}$, which is a dummy variable that takes a value of 1 if the firm has undertaken an IPO at date 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 total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and quarter-year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,[t-4,t-1]}$	0.002***	0.002***	0.004***	0.002**	0.002***	0.001**
	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
$LOA_{i,t-1}$		−0.002**	0.007***		0.005**	0.007***
		(0.0007)	(0.002)		(0.002)	(0.003)
$Num\,Drugs_{i,t-1}$		−0.00002***	0.000		−0.00001***	−0.00002***
		(0.000003)	(0.000)		(0.000004)	(0.0000)
Avg Peer Covariates	N	N	N	N	N	Y
Firm FEs	N	N	Y	Y	Y	Y
Quarter-Year FEs	N	N	N	Y	Y	Y
Observations	71,941	71,941	71,941	71,941	71,941	68,597
Number of Firms	2,139	2,139	2,139	2,139	2,139	2,131
R^2	0.0002	0.0004	0.100	0.103	0.103	0.114

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 1 if the firm has undertaken an IPO in year t, and 0 otherwise. $Prop\,Peer\,IPO_{i,t}$ is a continuous variable, which measures the proportion of the indication categories in firm i's drug portfolio for which a peer firm, defined as a firm which has a drug project in the same therapeutic indication category, has undertaken an IPO. $LOA_{i,t-1}$, is the average likelihood of approval for all projects in a firm's drug development portfolio. $Num\,Drugs_{i,t-1}$ is the total number of drug-indications currently in the firm's development portfolio. Average peer covariates include the lagged mean likelihood of approval and lagged mean number of drugs across each firm's peers. Firm and year fixed effects are included, as indicated. The regressions are run from 2000 to 2016. Robust standard errors are in parentheses, and are clustered at the firm level. 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)
$Peer\,IPO_{i,t-1}$	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
$LOA_{i,t-1}$		0.020**	0.027**
		(0.010)	(0.011)
$Num\,Drugs_{i,t-1}$		−0.00004	−0.00003
		(0.00004)	(0.00005)
Avg Peer Covariates	N	N	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Observations	14,645	14,645	14,492
Number of Firms	2,021	2,021	2,013
R^2	0.307	0.308	0.315