How Does VC Engagement Direct Startup Experimentation?*

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Abstract

We use granular data from the life sciences sector to study how VC engagement directs strategic experimentation. Active involvement by smaller, more focused VCs leads to early-stage pipeline prioritization, advancing a subset of projects while deprioritizing others. This strategy can produce "blockbuster" IPOs with mature lead assets but hurt startups by lowering the overall likelihood of exit. Startups backed by concentrated VCs progress more slowly in clinical trials on average and are more likely to discontinue projects due to prioritization rather than financial or quality concerns. We find that VC investors may prioritize therapeutic areas to align with limited investment horizons and to avoid portfolio cannibalization. Finally, we find that several VC-focused therapeutic areas, such as oncology, are less likely to receive final approval when backed by smaller or more specialized investors.

Keywords: strategic experimentation, investor engagement, pipeline prioritization, life science
JEL classification: G24, G11, O31, O32

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1 Introduction

The strategic experimentation process is inherently embedded in startup growth as a real option problem. Most entrepreneurs face significant uncertainty about the underlying technology, with limited chances of success. While *ex-ante* founders hedge failure risks by exploring various projects with the core technology, the availability of cash and R&D capital ultimately restricts the number of projects that can be advanced. This paper focuses on this project prioritization decision, where entrepreneurs decide when and which projects to pursue, arguing that active VC oversight exerts control to direct strategic experimentation. As a result, the investment and continuation of novel ideas might not necessarily be determined by a competitive contest about scientific potential, echoing the widely-cited "Entrepreneurship as Experimentation" perspective in Kerr et al. (2014).

We utilize granular data from the life sciences sector to study how venture capital (VC) engagement affects strategic experimentation decisions. Our key findings indicate that active involvement by smaller, more concentrated VCs drives early-stage pipeline prioritization, affecting the risk-return profile of entrepreneurial activities and innovation direction. While this approach can generate "blockbuster" IPOs with more advanced lead pipelines among startups that achieve successful exits, it also lowers the overall likelihood of exit by sacrificing the hedging benefits of diversified pipelines. Moreover, general partners may prioritize therapeutic areas that align with their own preferences, potentially sidelining projects with greater scientific promise or social value.

In this paper, we focus on VC investments in drug development startups for several reasons. First, the life sciences sector receives a substantial share of VC investment: more than 20% of annual VC funding is allocated to the biotech and healthcare industry, according to

a 2023 VC industry report.[1] Second, healthcare VCs typically insist on control provisions and place greater value on non-human intellectual property than on the founding team (Gompers et al., 2020), suggesting that disagreements over innovation direction may arise between investors and entrepreneurs. Third, there is growing interest in establishing life sciences "megafunds" that diversify risk by holding large portfolios of drugs based on uncorrelated core technologies (Lo and Thakor, 2022). However, limited partner bandwidth in such structures may reduce monitoring effectiveness, making it important to understand how fund engagement influences experimentation. Lastly, our data allow us to observe experimentation at the project level. Indeed, Ewens and Sosyura (2023) recently document that the loss of a VC director has inconclusive effects on startup patenting, highlighting the need for more granular measures of innovation activity.

We begin with a few stylized facts to clarify the institutional settings of entrepreneurship in the life sciences sector. First, we note the necessity of pipeline prioritization when progressing to later stages in the strategic experimentation process of innovative startups. Summary statistics from biotech IPOs in our sample reveal that these companies typically initiate around 12 projects for experimentation. However, by the time of the IPO, more than one-third of these projects are no longer active, with the majority still in the pre-clinical stage. On average, only one project reaches Phase 2, while approximately 1.3 projects advance to Phase 1. At the same time, a non-trivial fraction of startups go public with pipelines composed entirely of pre-clinical assets, reflecting substantial variation in prioritization strategies. These patterns highlight the importance of understanding both timing and selection in advancing the pipeline for startup growth.

Second, guided by the existing literature (e.g Bernile et al., 2007; Matusik and Fitza,

[1]For more details, see the article from Carta on December 19, 2023: https://carta.com/blog/vc-shifts-2023.

2012), we then characterize a startup's investor engagement using two straightforward measures, the size and the concentration of their VC's portfolio. Theoretically, researchers argue that a concentrated portfolio can be beneficial due to VC monitoring (e.g. Kanniainen and Keuschnigg, 2003; Fulghieri and Sevilir, 2009). Academic research and anecdotal evidence suggest that VCs frequently engage with their portfolio companies on financing and operational decisions. However, due to their limited capacity and human capital, expanding the size and scope of the portfolio can reduce the attention that VCs can devote to each startup. Consistent with this, we find that more concentrated VCs are more actively involved with their portfolio firms, as indicated by board representation and the replacement of founding teams.

We then ask whether a biotech founder prefers to be funded by smaller or specialized VCs, thereby revealing the underlying trade-off in investor choice. The third stylized fact shows that VC engagement is positively associated with the degree of pipeline prioritization among startups that reach IPO. Those financed by smaller or more focused investors are more likely to progress to later clinical phases during the pre-IPO window. These late-stage trials provide favorable information about drug technology, thereby mitigating adverse selection. Consistently, IPOs backed by these investors exhibit lower underpricing, highlighting the benefits of early prioritization. On the other hand, biotech startups backed by VCs with smaller or more focused portfolios are *ex-ante* less likely to achieve a successful exit via IPO. They are also less likely to be acquired, inconsistent with the view that specialized VCs pursue de-risked acquisition strategies. Instead, this pattern points to a higher likelihood of overall failure.

We interpret these stylized facts as evidence that VC-driven pipeline prioritization alters the risk-return profile of life science startups. Concentrating resources on a single lead

pipeline increases the likelihood of advancing a drug to a late clinical stage, conditional on a sequence of successful trial results, and attracting attention from primary market investors. However, given the substantial uncertainty inherent in developing novel technologies, this prioritization strategy naturally raises the risk of delay and even failure of other projects, thus limiting the ability to hedge across multiple projects. We further argue that VCs may not necessarily prioritize the project with the greatest scientific potential due to their constrained investment horizons and concerns over portfolio cannibalization. This argument is best exemplified by the anecdote of Acerta Pharma, an innovator of blockbuster blood cancer drugs, where investors prioritized a faster project to approval over a potentially more lucrative long-term strategy by replacing the founding team.

We test additional implications of prioritization, hypothesizing that, *on average*, greater investor engagement intensity slows drug project progress when only a few projects are prioritized. To establish this, we utilize comprehensive project-level development data from Cortellis, which tracks the progress of clinical trials across phases in a quarterly panel of approximately 78,000 observations. We follow the previous logic and create two baseline measures for VC engagement at the project level, but also explore alternative measures in the robustness check section. The first one is the logarithm of equal-weight portfolio sizes, defined as the average number of startups across all industries held by the VCs backing a focal project. Consistent with our hypothesis, a one-standard increase in the size measure is associated with an increased chance of progressing by 0.56%, equivalent to 43% of the unconditional quarterly progressing rate. Alternatively, we measure the concentration of each VC's investments using the Herfindahl-Hirschman Index (HHI) based on the allocation weights among portfolio startups. Conversely, the coefficients of HHI-based measures are negative and statistically significant, further suggesting that, on average, more VC

engagement is associated with slower innovation outcomes.

We acknowledge that the screening and selection in VC deals could confound our interpretation of the previous results. Larger or more diversified VCs may endogenously match with higher-quality biotech startups, creating a natural positive correlation between VC size and progress rate. To establish causal evidence, we need to obtain exogenous variations in VC portfolio sizes and diversification while holding the *ex-ante* matched VC-startup pair consistent to alleviate selection and then study the impacts of such variations on project-level innovation outcomes. Our instrument utilizes the staggered adoption of environmental and sustainable investment principles by an important category of VC limited partners (LPs), the state public pension funds. Life science startups are arguably neither green nor brown companies. We confirm that biotech startups held by VCs affected by these LP shocks do not experience changes in future funding frequency, and the exclusion restriction likely holds. The relevance of our instrument is supported by the finding that VCs exposed to sustainability goals significantly reduce investments in "brown firms" in the private market. We further argue that previously diversified VCs must reduce their portfolio size and concentrate their holdings, given an environmentally constrained investment opportunity set, shifting their attention towards the life sciences sector with relaxed monitoring capacity. This is indeed what we observe in the first stage, with the t-statistics of the instrument being 5.8 and 4.0. Consistent with our OLS results, the second-stage coefficients for size-based measures are positive and significant, while the coefficients for HHI-based measures are negative and significant. These results again suggest that after a life-science startup's existing VCs become more engaged, its R&D speed significantly decreases.

We further support the interpretation that VC engagement directs project prioritization

in two ways. First, we explore scenarios where VCs have stronger incentives to advance a focal project, utilizing the "winner-picking" tendency documented in the life sciences industry (Robinson, 2008). We define a project as "high priority" if it is strictly more advanced in development than all other projects in the same developer's pipeline. We find that the slowing-down effects of VC engagement are twice as large in the low-priority group and disappear entirely in the high-priority group. Second, we examine the subset of drug projects that are explicitly discontinued. The data provider categorizes these reasons into pipeline priority, lack of efficacy, lack of funding, and other reasons. Consistent with our hypothesis, we find that projects are more likely to be discontinued for prioritization reasons when the company is backed by more focused VCs. In contrast, we find no significant correlation between VC engagement and discontinuation due to funding or efficacy. These null results alleviate the concern that larger or more diversified VCs are simply more willing to fund costly experimentation. Finally, we find no significant differences in project quality by VC size or concentration, reinforcing the view that investors face substantial challenges in screening early-stage innovation (Kerr et al., 2014).

How can an active VC find project prioritization optimal while the withheld project remains valuable to the startup? We argue that conflicted interests arise between investors and founders due to differences in investment horizons and the risk of portfolio cannibalization. First, VCs often face shorter fund life cycles and may need to exit before long-term projects generate credible signals, exposing them to underpricing risk. As a result, they may deprioritize high-uncertainty or slow-to-develop projects. We find that the slowing effects of engagement are concentrated in projects funded by older funds nearing liquidation and in therapeutic areas with longer development timelines. Second, when a startup explores multiple disease targets, it may compete with other commonly owned firms, lead-

ing to cannibalization through overlapping R&D, higher trial costs, and reduced market power. We show that VC engagement tends to consolidate therapeutic focus within a single portfolio startup: drug projects backed by more specialized VCs are more likely to be developed within the same firm and less likely to face internal competition.

We perform a series of robustness checks to validate our baseline results. First, we show that our findings hold across the VC size and performance distribution, rather than being driven by small-size outliers. Second, we examine founder turnover as a direct outcome of VC intervention and find that the negative effect of VC concentration on research progress arises primarily when the founding team is replaced, consistent with an engagement channel. Third, we replicate the analysis using each startup's lead VC rather than the investor syndicate and document similar results. Our baseline specifications also incorporate investment-weighted measures to account for heterogeneity in investor control. Fourth, we confirm that our findings are robust to alternative definitions of VC concentration at the industry or geographic level. Fifth, we verify that all results replicate using investment data from VentureXpert instead of PitchBook. Finally, we implement the alternative identification strategy from Bernstein et al. (2016), which exploits the introduction of direct flights as an exogenous shock to VC involvement. We find that increased lead-VC engagement slows the progress of strategic experimentation in early stages,[2] further supporting our interpretation of VC engagement as a key determinant of innovation outcomes.

Before we conclude, we discuss the implications of our results in Section 4.4. Our findings do not necessarily imply that smaller or more specialized VCs underperform in the life sciences sector. Our last two stylized facts suggest that these investors pursue a high-

[2]In contrast, on-site monitoring has positive effects in later stages of development, where commercialization becomes more central. This is consistent with Bernstein et al. (2016), who find increased patenting activity in later-stage ventures.

risk, high-return strategy: achieving higher payoffs per successful startup while accepting lower overall exit rates. This approach is consistent with a preference for backing potential "superstar" firms, aligning with recent survey evidence on voting behavior by Malenko et al. (2024). Indeed, we show that their expected payoff ratios are comparable to those of large or more diversified VCs. However, this similarity in performance masks substantial heterogeneity in experimentation strategies driven by investor characteristics. We find that the impacts of VC involvement vary by therapeutic area: concentrated VCs are particularly effective in advancing hematology projects, while oncology startups, despite being central to the VC-financed life science sector, tend to progress more slowly and are less likely to reach final approval when backed by smaller or more specialized investors. These patterns echo concerns raised by Lerner and Nanda (2020) that the VC model may favor only a narrow subset of technological progress. We believe that the emergence of more patient capital, including impact funds, royalty financing, and megafunds, could potentially help fill the gaps left by traditional financing instruments in this market. Accordingly, life science startups should aim to match investors whose characteristics align with their therapeutic focus and stage of development. No single investor type is universally optimal, whether generalist or specialist, large or small.

Our focus on project prioritization aligns with the experimentation view of entrepreneurship (Kerr et al., 2014; Ewens et al., 2018). VC financing is optimally structured into stages for interim signals, creating a real option problem for the continuation and termination of innovative projects (Bergemann and Hege, 2005; Manso, 2011). Existing theoretical literature argues that VCs may hold up startups for rent exploitation by threatening funding discontinuation, thereby hurting experimentation incentives (Fulghieri and Sevilir, 2009; Inderst et al., 2007). Instead, our paper highlights VCs direct innovation outcomes by se-

lectively prioritizing projects that match their investment preferences. While this direction effect has been noted by Kerr et al. (2014) and Lerner and Nanda (2020), to our knowledge, this paper is the first empirical study to test and confirm this hypothesis. Ewens and Malenko (2020) emphasize the emergence of VC–entrepreneur conflicts during the middle stage of startup development, which closely aligns with the timing of project prioritization decisions in our setting. Additionally, related literature documents that VCs may pass business cycle risks to the innovative sector (Nanda and Rhodes-Kropf, 2013, 2017). Howell et al. (2020) find that innovation conducted by early-stage VC-backed firms is of lower volume and quality in recessions. Unlike the financing channel, our paper shows that increased VC involvement could slow down innovation in certain areas due to prioritization.

Our paper is also related to the prior research on portfolio size, concentration, and VC engagement. Early evidence suggests that VCs limit both fundraising frequency and fund size (Gompers and Lerner, 1996), and top-performing VCs voluntarily choose to stay smaller (Kaplan and Schoar, 2005). Various research studies have examined the optimal portfolio size using trade-off theories. Larger portfolios can be beneficial due to diminishing returns of advice per firm (Kanniainen and Keuschnigg, 2003), diversification of idiosyncratic risks (Bernile et al., 2007), and *ex-post* bargaining advantage and resource reallocation (Fulghieri and Sevilir, 2009). However, a trade-off exists because a smaller portfolio allows the VC to spend more effort on each startup.[3] While we agree with the aforementioned value-adding services by VC monitoring, our empirical results highlight the heterogeneity of VC engagement in affecting experimentation. Our results also echo the inconclusive empirical evidence on how VC specialization impacts startup performance. Gompers et al. (2009) shows that when the individual venture capitalist is

[3]Note that Fulghieri and Sevilir (2009) also argues that a small portfolio ensures that VCs will not threaten to divert resources to extract *ex-post* rents.

a specialist, the performance difference between the specialized and general VC firms is minimal. Portfolio diversification also encourages managers to take on riskier projects and facilitates knowledge sharing between portfolio firms (Buchner et al., 2017; Humphery-Jenner, 2013; Matusik and Fitza, 2012). None of these papers focuses on the strategic experimentation of innovative ideas as we do.

Our paper is also related to the strand of literature on financing novel and radical drug innovation. Existing literature documents the shifted direction of innovation towards short-term and less innovative drugs through two channels. First, Budish et al. (2015) argue that drugs taking longer to complete clinical trials will enjoy shorter intellectual property rights after commercialization due to a fixed patent term. Second, Krieger et al. (2022) show that risk aversion prevents pharmaceutical companies from optimally investing in novel drug development. Unlike their findings, we focus on the conflict of interest between investors and developing companies. Lastly, our paper falls into the broad literature on the impacts of external financing conditions on drug innovations, such as mergers and acquisitions (Cunningham et al., 2021; Phillips and Zhdanov, 2013), IPOs (Aghamolla and Thakor, 2021), and licensing (Hermosilla, 2021; Hammoudeh et al., 2022).

2 Institutional background and data

2.1 The Life sciences industry

Drug development involves a structured regulatory process that firms must navigate before launching the product on the market. In the US, the FDA evaluates candidate molecule structures (labeled by the generic name of drugs) for specific diseases and symptoms (known as indications) based on their safety and efficacy. The drug development process

consists of several phases. The initial phase involves the discovery stage and pre-clinical stage, where thousands of molecules are screened, and only a few promising candidates undergo testing in laboratories and on animals. Then, drugs move to be tested on human beings. In Phase 1, the safety and efficacy of a drug are evaluated in a small group of 10 to 50 volunteers. If a drug proves safe in humans, it advances to Phase 2 trials, involving a larger sample of 50 to 200 volunteers to evaluate both safety and efficacy. Drugs with robust Phase 2 evidence move on to Phase 3 trials, where safety and efficacy are rigorously tested in a large sample of 200 to 3,000 volunteers.

Despite their high social value, the development of novel drugs is characterized by high research and development costs, lengthy development timelines, and large scientific uncertainty. The average cost of getting a new drug into the market between 2009 and 2018 was $1.3 billion (Wouters et al., 2020). The journey of clinical development can take from five to more than twenty years, with a median of over eight years (Brown et al., 2022). As of June 2023, according to Cortellis data, less than 18% of drugs that undergo clinical trials ultimately receive approval from the Food and Drug Administration (FDA) by June 2023.

VC-backed startups are active drivers in drug development, and their activeness has been increasing over time. As per Pitchbook and Cortellis data, the percentage of newly approved drugs from VC-backed originators rises steadily from 2000 to 2020. The time-series average is 8.14% from 2010 to 2015 and increases to 13.27% from 2016 to 2020. In 2021 alone, Pitchbook-covered biotech companies raised a total of $81.76 billion in VC funding rounds. They assist drug development teams in navigating the "valley of death," an intermediary stage where the science has progressed beyond research funded by federal sources but remains too premature for significant involvement from large pharmaceutical

companies. In the life sciences sector, VCs' impact goes beyond financial contributions; they actively engage in the scientific development process (Gompers et al., 2020). For example, Atlas Venture adopted a venture creation model that assists startups in designing killer experimentation, exploring potential pivots, attracting talents, and assessing market interest from big pharmaceutical companies and other investors.[4]

2.2 Drug development data

We construct a project-level quarterly panel from the Cortellis Drug Discovery Intelligence Platform following Li et al. (2023), Guenzel and Liu (2023), and Krieger et al. (2022). Cortellis aggregates clinical trial data from various public resources beyond the FDA clinical trial registries, including scientific publications, academic presentations, patent filings, company press releases, and others. This comprehensive dataset covers the drug's originator company, indications, and both current and historical development status, among other details. Notably, Cortellis provides updates on when an indication progresses to the next clinical phase or is discontinued in the current phase, enabling us to trace the evolution of each indication's development status over time.

Following the institutional convention, each project is a sequence of trials studying a molecule structure's potential for a given indication, i.e., a drug-indication combination. The rationale is that the FDA will separately approve a given product's commercialization targeting various indications. Logically, different diseases require different endpoints and indicators to prove safety and efficacy. Developing companies have to design different sequences of trials for approval. By extracting project-level development records from the

[4]For more details, see the article from Fortune on August 15, 2019: The Creation Of Biotech Startups: Evolution Not Revolution.

Cortellis database, we create a drug-indication quarterly panel documenting each project's furthest active stage (e.g., Phase 1) in a given quarter. Building on the development status, we introduce a dummy variable *Next Phase* as our focal outcome variable to indicate whether the project will progress to subsequent phases in the following quarter. For example, *PRX-8066* is the generic name of a drug developed for multiple types of lung diseases, such as lung infection and MRSA infection. In our panel data, the *PRX-8066*-pulmonary-fibrosis combination is constructed as a separate project from the *PRX-8066*-pulmonary-hypertension combination. In May 2005, the pulmonary hypertension project progressed to Phase 1 clinical from discovery and further progressed to Phase 2 clinical in June 2006. In this case, we code *Next Phase* for *PRX-8066's* pulmonary hypertension project as one at 2005Q1 and 2006Q1. We consolidate three pre-Phase-1 statuses in Cortellis "discovery," "pre-clinical," and "clinical" into a single pre-clinical stage and ignore progressing between pre-Phase-1 statuses. These pre-clinical status designations are more arbitrary decisions by developing companies and may not represent significant scientific milestones. For each project, our quarterly panel includes the quarters when the drug has active trials and excludes records with terminated or perfected development status.[5]

2.3 VC investment data

We obtain data on VC deals from 2000 to 2020 from Pitchbook, which sources private equity, venture capital, and mergers and acquisitions data from regulatory filings, press releases, company websites, financial statements, and industry professionals. For each transaction, Pitchbook details the investor company, primary investor type, investee com-

[5]These statuses include "outlicensed", "no development reported", "discontinued", "withdrawn", "suspended", "pre-registration", "registered" and "launched."

pany, deal type, investment amount, investment date, type of stock, etc. We collect VC data from Pitchbook in view of its granularity and accuracy. In the online appendix, we show that our baseline regression results are robust using the alternative VentureXpert data.

We focus on VC deals made to US startups and exclude non-VC deals, VC deals made by non-VC investors, and VC deals made to companies headquartered outside the US. Next, we match the Pitchbook investees and Cortellis drug companies in the following steps. First, we utilize official company websites to match Cortellis drug companies with Pitchbook startups. Second, we proceed with exact company name matching when website matching is completed. Third, we implement fuzzy matching for company names and manually review all potential matches for those not matched in the above steps. In so doing, we are able to pin down 1,387 unique US drug companies that have ever received VC funds from 2000Q1 to 2020Q4 and also appear in the initial panel we construct in Section 2.2.

We then develop two variables to proxy the engagement intensity of a VC investor in a given quarter based on its investment activities in the past ten years. The first measure is portfolio *Size*, defined as the unique number of startups across all industries in which this VC has invested during this window. VCs typically limit the number of startups in their portfolios because they would otherwise devote less time and effort to each company when investing in more firms (Bernile et al., 2007; Fulghieri and Sevilir, 2009). Ewens et al. (2013) argue that the requirement of monitoring efforts restricts the size of the portfolio and the scope of diversification, exposing VC compensations to idiosyncratic risk. We also construct the second measure as an *HHI* index, reflecting the concentration of a VC's allocation weights across portfolio startups. A VC investor's *HHI* index is the sum of the squares of the percentages of its investments in each drug company over its all

investments for drug companies during the 10-year rolling window. A higher *HHI* indicates greater concentration in a small number of startups, suggesting a more specialized focus.

In our drug project quarterly panel, each startup may have multiple VC investors in a given quarter. Therefore, we need to aggregate the above measures across various investors at the startup level. For each matched drug company in a given quarter, we track all VC investors that have invested in this company over the past five years and average both *Size* and *HHI* equally. As a robustness check, we alternatively create measures weighted by the total deal amounts from each investor to reflect differences in the control powers. Specifically, for drug startup i in a given quarter t, we track all VC deals invested in startup i from quarter $t-19$ to quarter t (i.e., five years). Next, we aggregate the *Size* and *HHI* measures from the startup-VC-quarter level to the startup-quarter level. *Ln(Size)* is the (logarithm of) equally-weighted VC sizes, and *HHI* is the equally-weighted VC HHI index of a given startup at the focal quarter. *Ln(VW-Size)* and *VW-HHI* are similarly defined, except that the corresponding measures are weighted by the total amount of investments in the past five years by each VC. By integrating these startup-level measures with the drug indication development data, we arrive at a drug-indication-quarter panel containing over 90,000 observations on drug indication development status and VC engagement intensity measures from 2000Q1 to 2020Q4.

2.4 Other data

A VC's control over a startup diminishes substantially following an exit via IPO or acquisition. To identify these exit events, we collect IPO and acquisition dates from SDC Platinum and supplement missing IPO dates using Jay Ritter's dataset. After removing post-exit observations for matched drug companies, our final panel consists of 77,874 observations.

To characterize the oversight from VC investors, we follow Gompers et al. (2023) and Jang and Kaplan (2023) and collect board entrance data for matched drug companies from Pitchbook. Specifically, for a drug company in a given quarter, we check whether there are any new additions to the company's board representing certain VC investors who have previously invested in this company. We then construct a dummy variable *New Board*, which takes the value of one if a drug company gains a new board member from its VC investors in a given quarter and zero otherwise. In addition, we track the employment history of founding team members to examine whether any founders depart from the startup. The goal is to identify founder turnover as a potential signal of internal conflict between investors and the founding team.

2.5 Summary statistics

Table 1 reports the summary statistics for our drug development variables and VC engagement intensity measures from 2000Q1 to 2020Q4. Consistent with the scientific difficulty, around 1.3% of the drug indications unconditionally make it to the next phase in a given quarter. The typical drug company in our sample has an average investor size of around 38. If these investors invest equally in all portfolio startups, then the hypothetical average HHI would be around 0.03 ($= 38 \times (1/38)^2$). Instead, the average weighted HHI is about 0.23, suggesting that VCs rationally allocate additional funding towards certain startups and hold back others in the continuation decisions. Experimentation in the life sciences sector is costly, with a typical company receiving about $35.7 million in a five-year rolling window. In the appendix Table IA.1, we split the sample into early-stage (pre-clinical and Phase 1) and late-stage (Phase 2 and Phase 3). The success rate of clinical trials, not surprisingly, reduces (to 0.7%) in the later phases. Late-stage clinical trials appear to be more

expensive, receiving about $38 million every five years.

3 Stylized facts

In this section, we document four descriptive observations in the life science entrepreneurial sector to motivate and guide our empirical studies. These facts do not necessarily imply causal relations, and we defer to more rigorous analyses in later sections. They provide unique institutional knowledge to help us understand the empirical setting.

Fact 1: Life science startups can only prioritize a limited number of drug projects to a later clinical trial stage during the strategic experimentation process before the IPO.

In Table 2, we present the characteristics of drug projects for the startups in our sample that successfully exited by going public. A typical startup actively experiments with ideas, initiating almost 12 projects throughout its pre-IPO life cycle. There are two explanations for this high degree of experimentation. Scientifically, many indications share common pathways, allowing one molecular structure to be effective for multiple diseases. Additionally, startups explore various projects from a hedging perspective, given the substantial risk of failure in this process. Indeed, about one-third of the projects are suspended by the time of the IPO, resulting in an average active pipeline size of 7.3.

The existence of project prioritization in later stages becomes evident when we examine the stages of the active pipeline. The majority of projects (67.1%) do not progress and remain in the pre-clinical phase, i.e., not being tested on human bodies. On average, a typical IPO startup will have just over one Phase 2 project and 1.3 Phase 1 projects. Progressing a project to Phase 3 is almost impossible for startups. These summary statistics highlight two key aspects of prioritization. First, drug experimentation requires sub-

stantial investments in both cash and time, effectively limiting the number of projects that can feasibly progress. Second, life science IPOs substantially increased following the Jumpstart Our Business Startups (JOBS) Act in 2012. The preference of primary market investors shifted toward biotech companies with products earlier in the FDA approval process (Dambra et al., 2015; Lewis and White, 2023). Consequently, there is substantial variation in pipeline maturity at IPO as the median number of Phase 1 and Phase 2 projects is zero. A non-trivial fraction of startups enter the public market with pipelines composed entirely of pre-clinical assets. This heterogeneity suggests that startups need to decide the optimal timing of prioritization and the choice of prioritized projects when moving to the next phase of clinical trials.

Fact 2: Smaller or more focused VCs are more actively engaged in overseeing startups in the life sciences sector.

The literature argues that one benefit of a concentrated VC portfolio is to ensure the overseeing efforts of general partners given limited human capital (e.g. Bernile et al., 2007; Fulghieri and Sevilir, 2009). We first test this hypothesis in our sample using the following regression: whether the startups observe VC investors joining their company board.

$$New\,Board_{k,t} = \alpha + \beta VC\,Engagement_{k,t} + \Phi X_{k,t} + \gamma_k + \delta_t + \epsilon_{k,t}, \tag{1}$$

We perform the analysis of Equation (1) at the startup quarterly sample. $VC\,Engagement_{k,t}$ indicates the VC engagement intensity measures. Besides company and time fixed effects, we further control for VC investment amounts and a company's active portfolio size in $X_{k,t}$. In Table 3 columns (1) and (2), $New\,Board_{k,t}$ is one if drug company k has any new board members from its VC investors at time t. The coefficient estimate of *Ln(Size)*

in column (1) is negative and statistically significant at 1%, suggesting that larger VCs are significantly less likely to take the board seats of their portfolio startups. Consistently, the positive and significant coefficient estimate of *HHI* in column (2) also suggests that VCs with more diversified portfolio companies are less likely to sit on their investing drug company's board.

An alternative way to measure VC oversight is by examining turnover within the founding team. VCs in the life sciences sector are known for focusing on the underlying science and technology rather than the original team members, as evidenced by the survey in Gompers et al. (2020) and the anecdote later in this section. Founder replacement is a particular strategy for VCs to utilize control power when disagreements arise with the founding team. However, this replacement can be costly for the startup's innovation and operations. Supporting this hypothesis, Table 3 columns (3) and (4) show that smaller, more concentrated VCs are associated with a higher frequency of turnovers among the initial founding team.[6] Overall, our results align with recent evidence by Fu (2024), which uses cell phone signals to show that larger VCs monitor less per deal across all industries.

Fact 3: Conditional successful exits, life science IPOs invested by more active VCs have more late-stage projects and lower underpricing.

Fact 3 connects the previous two by asking how VC engagement shapes project prioritization and, in turn, influences pipeline maturity at IPO. To explore this, we conduct cross-sectional correlation analyses linking investor behavior to the clinical progress of startups at the time of exit. For each IPO, we first measure R&D performance by identifying whether the startup has at least one Phase II or later project or by counting the total number of such projects. To quantify the general degree of VC engagement over a

[6]Table IA.2 reports results using value-weighted size and HHI measures, which are quantitatively similar to those reported in Table 3.

startup's life cycle, we compute time-series averages for the *Size* and *HHI* measures. Figure 1 illustrates the correlation between investor oversight and clinical progress at the time of exit. Startups backed by smaller, more focused VCs tend to have more advanced lead pipelines. We interpret this as evidence that these VCs drive early pipeline prioritization, concentrating funding and resources on the lead project to accelerate its progress. When these lead projects indeed generate positive trial results, they resolve scientific uncertainty and mitigate adverse selection. Consequently, such IPOs are also associated with lower underpricing, as measured by first-day IPO returns.

Fact 4: Life science startups invested by more active VCs are *less* likely to exit through IPO or M&A.

The previous fact only focuses on the "winners" from the prioritization strategy. We now move to the full sample of startups by studying how this strategy affects the chance of successful exits through IPO or M&A. Figure 2 best visualizes Fact 4 using a simple mean comparison, where we sort all startups into 20 equal-sized buckets. Within each bucket, we calculate the fraction of IPO exits among all startups in it. Panel A exhibits an obvious increasing relation: startups invested by larger funds are more likely to go public. The group of startups held by the smallest VCs exit via IPO by a chance of 2.8%, which is eight times smaller than those held by the largest investors (22.9%). Consistently, the relation is starkly reversed in Panel B, suggesting that more concentrated VCs see fewer IPOs in their portfolio companies. A similar pattern is documented for acquisition outcomes in Panels C and D.

There exist many potential non-exclusive explanations for this observation. Larger and more diversified VCs may have sufficient funding and provide additional capital for startups. In Table 4, we explicitly control for the average quarterly investment amounts

received by the startup. Indeed, larger capital inflows significantly increase the chance of IPOs. However, columns (1) and (2) show that the previous relationship remains robust, even controlling for financing amounts. Alternatively, larger VCs may receive better deal flows and match with high-quality startups. In Table 4, we include additional fixed effects such as the initial therapeutic areas, founding times, and locations to absorb the unobserved heterogeneity across startups.[7] Lastly, it is possible that smaller, more specialized VCs pursue early-stage "de-risking" strategies with the intention of exiting through M&A rather than IPO. However, columns (3) and (4) show that VC engagement is also associated with significantly fewer M&A exits. When combining IPO and M&A exits, the magnitude of the coefficients in the last two columns nearly doubles relative to the first four. This pattern suggests that VC engagement reduces the overall likelihood of successful exits, rather than simply shifting the mode of exit from IPO to acquisition.

Although technology quality and labor skills are largely unobservable in the data, we also find that VC size and concentration are not correlated with the project's disease area (Figure IA.1) or the educational background of the founding team (Figure IA.2). Put differently, it is *not* the case that smaller VCs are investing in startups with projects in riskier disease areas or with entrepreneurs lacking life sciences training. Note that Kerr et al. (2014) suggests that even conditional on initial VC investments, it is hard to predict the final success of startups. Moreover, it is *ex-ante* unclear whether larger or more diversified VCs will match startups with better qualities, as suggested by Kaplan and Schoar (2005). It is possible that good deals are scarce, and VCs face diseconomies due to decreasing quality when growing in size.

Summary: We argue that VC engagement leads to early-stage prioritization of lead

[7]For the therapeutic area classification, we follow the International Classification of Diseases 9th Revision (ICD-9), which is a code set used to classify diseases, symptoms, and other factors.

pipelines, which alters the risk-return profile of life science startups. Concentrating resources on a lead project allows it to become more advanced by the time of IPO. However, this strategy is inherently risky, given the challenges of developing novel drugs. If the lead project yields negative trial results, the remaining pipeline is often too underdeveloped to attract primary market investors. A natural consequence of pipeline prioritization is that VCs influence the direction of innovation in life sciences. For example, VCs may concentrate on a set of drugs that are easier to commercialize in the short term due to limited investment horizons. They may also delay a startup's progress if its success could cannibalize the pipeline of other companies in their portfolio, potentially reducing the fund's overall valuation. As a result, active VC engagement may, in some cases, slow innovation in neglected therapeutic areas.

This prioritization strategy is evident in the story of Acerta Pharma, a startup that originated the later-approved blockbuster Bruton's tyrosine kinase (BTK) inhibitor drug acalabrutinib (commercialized as Calquence). Acalabrutinib was initially investigated for multiple blood cancer indications, including mantle cell lymphoma (MCL) and chronic lymphocytic leukemia (CLL). In 2014, the company was considering moving these trials toward Phase 2. The founding CEO wanted to continue the trials of CLL, the most common type of leukemia in adults. However, acalabrutinib's competing drug ibrutinib (Imbruvica) had already been fully approved by the FDA for CLL, and acalabrutinib had to demonstrate significant improvement against ibrutinib in a head-to-head Phase 3 trial for approval. Although the founding CEO was confident in the projected results based on scientific knowledge, this trial would require tracking patient survival for many years. Instead, the lead investor, which was a small fund focusing on blood cancers, wanted to prioritize MCL, a rare disease eligible for accelerated approvals and not requiring compar-

ison with ibrutinib. The founding CEO was ultimately replaced due to the disagreement. In fact, the investors had already forced the CEO to prioritize acalabrutinib in the blood cancer space and move away from autoimmune diseases such as rheumatoid arthritis. This internal turnover held back the overall progress of the startup, leading it to be acquired by the pharmaceutical company AstraZeneca PLC in 2015. Following the prioritization strategy, the FDA granted Calquence accelerated approval for use in MCL in October 2017. However, the initial annual sales were below $100 million due to the small market of MCL as a rare disease. Consistent with the founding CEO's prediction, acalabrutinib successfully completed the head-to-head Phase 3 trial and received full approval for CLL in November 2019. Sales skyrocketed afterward, with Calquence recording annual sales of $2.5 billion in 2023.

4 Empirical analysis

4.1 Evidence of project prioritization

We hypothesize that a higher VC engagement intensity will, on average, slow down drug project progress when only a small number of projects are being prioritized. A direct implication is that a typical drug project will become less likely to progress when its VCs are more focused and engaged. We make use of the quarterly project panel from Cortellis to test this implication. In particular, we focus on the clinical trial progression of drug indications developed by VC-backed companies and estimate the following baseline regression:

$$Next\,Phase_{i,j,k,p,t} = \alpha + \beta VC\,Engagement_{k,t} + \Phi X_{k,t} + \gamma_{i,j} + \delta_p + \zeta_t + \epsilon_{i,j,k,p,t} \quad (2)$$

where $Next\,Phase_{i,j,k,p,t}$ is a dummy variable equal to one if indication i of drug j at phase p from company k enters next phase at time $t+1$. $VC\,Engagement_{k,t}$ represents one of the VC engagement intensity measures: $Ln(Size)_{k,t}$, the natural logarithm of the simple mean of company k's investing VC portfolio sizes at quarter t and $HHI_{k,t}$, the simple average of the HHI index for company k's investing VCs at quarter t.[8] We control for additional startup-level characteristics that potentially affect project progress in $X_{k,t}$. $Ln(VC\,Amount_{k,t})$ is the logarithmic aggregated investment amount for company k's VC investors at time t, controlling for funding sufficiency. $\#\,Developing\,Drugs_{k,t}$ denotes the number of drugs under active development from company k at time t, controlling for the pipeline size. Besides, we include granular fixed effects to absorb unobserved heterogeneity at the project level. $\gamma_{i,j}$ is the drug-indication fixed effect, absorbing the scientific potential of each molecule targeting a given therapeutic field. δ_p is the phase fixed effect, reflecting the fact that progressing becomes increasingly difficult in later stages. Lastly, ζ_t is the year-quarter fixed effect, which accounts for time-varying scientific changes. Throughout the paper, we double-cluster the standard errors at the ICD-9 and year-quarter level for project-level estimates. In Table IA.3, we show that the results remain significant if we replace the ICD-9 clustering with the company level or the ICD-chapter level.[9]

Table 5 presents the regression results of Equation (2). Consistent with our predictions, we find that the coefficients of average VC sizes in columns (1) and (2) are positive and significant, suggesting that drug projects backed by larger VCs are more likely to pass clinical trials. Economically, column (2) implies that a one-standard-deviation increase in

[8] In the robustness section, we show that our results are robust to using value-weighted measures or simply focusing on the lead VCs.

[9] The ICD-chapter is a group of ICD-9 codes that share broader medical similarities. For example, Vitamin A deficiency (ICD-9 264) and Vitamin D deficiency (ICD-9 268) both belong to the chapter "Nutritional Deficiencies."

the *Ln(Size)* (i.e., 1.12 units increases in the sample) raises the chance of progressing to the next phase for drug projects developed by VC-backed drug companies by 0.56% ($= 0.005 \times 1.12 \times 100\%$), equivalent to 43% of the unconditional average probability of progressing to the next phase. Conversely, the coefficients of average *HHI* in columns (3) and (4) are negative and significant, further suggesting that less VC concentration is associated with faster innovation outcomes. Overall, these results support the interpretation that VC engagement slows down their portfolio companies' project progress on average while prioritizing a few projects.

Other confounding characteristics of VCs could have driven the above results. For example, larger or more diversified VCs may be more reputable and have high-quality human capital. As a result, they observe better deal flows and match with better startups. Alternatively, they may have deeper pockets and support more expensive and advanced research designs. The ideal experiment is to hold the VC-startup matched pair constant to alleviate *ex-ante* sorting concerns and then exogenously let the VC investors become more active and study the downstream effects on innovation progress. To implement this research design, we make use of an instrumental variable (IV) analysis. Our instrument utilizes the state-level variation in incorporating environmental and sustainable principles into their public pension funds' investment process. Public pension funds have been active in socially responsible investments for a long time for various reasons (Hong and Kacperczyk, 2009; Dimson et al., 2015). Sixteen states explicitly started to incorporate sustainability into their investment goals in a staggered manner from 2013 to 2020. This emerging trend in investment practices has incurred a significant impact, ultimately leading to a March 2023 Senate bill trying to prevent pension fund managers from including factors such as climate change in their investment decisions. President Biden later rejected this bill as the first

veto of his presidency.

Below, we explain how we construct the instrumental variable based on the variation in adopting sustainability as an investment goal. First, in a given year, we hold each focal drug company's VC investors constant, keeping those who had invested before any sustainability shock exposure. In other words, if a biotech company is first invested in by a VC after an LP shock, we exclude this VC from the instrument construction. Second, for each remaining VC, we determine whether at least one of its LPs has adopted a sustainability goal by a given year. Lastly, we create the instrument at the drug company level by calculating the fraction of treated investors over all its holding VCs. Because we use two endogenous measures of VC engagement, we weight each affected investor by its pre-shock size or by its pre-shock diversification (one minus the HHI), corresponding to the respective measure.

We argue that our IV is relevant because VCs exposed to the sustainability mandate face a more constrained investment opportunity set, leading to smaller and more specialized portfolios in subsequent funds. This reduced scope likely increases the monitoring capacity per firm, enabling general partners to allocate more attention to monitoring existing startups. We validate this relevance condition in several steps. First, our IV requires a repeated financing relationship between state pension LPs and the VC firm. Table IA.4 in the appendix shows that, conditional on investing in a VC fund, a state pension LP has over a 70% likelihood of committing to another fund by the same VC and a 45.7% probability of doing so at the next fundraising event. Furthermore, this persistence is independent of whether the LP has adopted ESG goals: the coefficients of the treatment variable have insignificant impacts on a state pension LP's propensity to participate in future VC fundraising. Second, it requires to confirm that the preference of state pension LPs directly impacts

investment decisions made by general partners. State public pension funds are among the most important LPs in the venture capital industry due to the adoption of prudent investor rules (González-Uribe, 2020; Andonov et al., 2018). We present evidence on the investment strategy changes of the "treated" VCs in our sample in Table IA.5. When investing in new startups, these VCs significantly decreased allocations in the energy sector, both in terms of the number of firms invested in (by 0.8%) and the amount of capital allocated (by 2.4%), indicating a holding-reduction strategy in new funds. Notably, this concentration is not solely a result of shifting away from the energy sector. As Figure 3 shows, 5 out of the 7 sectors, with 2 being statistically significant at the 5% level, experience a reduction in the number of new startups being invested in. These patterns suggest that affected VCs are not reallocating capital into unrelated sectors, likely due to constraints on deal flow or supply. Nor do they appear to increase deal size to compensate for the narrower scope, as total capital allocated also declines, consistent with heightened risk-management concerns.[10] Finally, we show that affected VCs exhibit more intensive involvement in their existing biotech portfolio firms, consistent with increased monitoring capacity per startup. Table IA.6 shows a significant increase in founder turnover following the ESG-driven shock to their investors, suggesting greater managerial intervention and oversight.

Following the previous results, Table 6 reports the 2SLS regression results using instrumented VC engagement intensity measures. The first two columns present the first-stage results. In line with our expectation, these columns report significant coefficients with pre-

[10]This result aligns with the different sustainable investment strategies employed by state pensions in the public versus private markets. For example, MainePERS takes a passive approach in the public market by holding index funds and relying on the ability to "actively engage with company management, particularly through the proxy voting process." In contrast, before investing with any private asset manager, MainePERS completes a due diligence checklist of ESG-specific items, identifies and monitors risk factors, and requires and reviews an ESG policy from the funds. For details, see the "Environmental, Social, and Governance Report," 2017 Edition by MainePERS.

dicted signs, suggesting that the exposure to the pension funds' ESG investment requirements has a positive impact on VC concentration, both in terms of the number of firms and the HHI measures. The t-statistics for our IV are 5.8 and 4.0 across the first stages, with *F*-statistics all well above 10. These tests provide strong support for the relevance condition.[11]

The exclusion restriction condition requires that after a VC firm's state pensions adopt sustainable investment, this adoption affects the innovation process of that VC's portfolio firms only through engagement. Our instrument follows the logic of Townsend (2015) and Kempf et al. (2017), who study how a focal firm responds when commonly owned firms in other sectors undergo significant shocks. We utilize the fact that a biotech startup's VC investors will shift their attention away from "brown firms" if they face sustainability pressures from state pension LPs and allocate that attention toward life science firms. The key challenge to our exclusion restriction is that this shift in investment interest might be associated with a capital influx into life sciences, leading to two concerns. First, existing biotech startups may receive additional funding to support more expensive trials. Second, being forced to concentrate on life sciences, affected VCs may invest in a larger amount of new firms of lower quality.

However, the life sciences sector is arguably neither green nor brown. First, Table IA.7 shows that "affected" existing startups do not receive additional follow-up funding from their VCs, and we find no significant evidence that the instrument correlates with any changes in funding patterns. Moreover, even if affected VCs did supply additional capital to the existing portfolio biotech startups, we would expect better innovation outcomes as-

[11]The coefficients of our instrumented variables ($\widehat{Ln(Size)}$ and $\widehat{HHI}$) in the second stage regression remain statistically significant at the 5% level and 10% level, respectively, after adjusting the critical values of the *t*-statistics by the size of the first-stage *F*-statistics as recommended by Lee et al. (2022).

sociated with concentration. Our hypothesis predicts the opposite, so this channel works against us. Second, by construction, we define the instrument only for startups that were already in the affected VCs' portfolios before the shock, meaning our results are not directly challenged by any potential quality shifts among *new biotech startups* invested after the shock. Furthermore, Table IA.5 indicates that affected VCs' preferences for new biotech startups remain largely unchanged after adopting the sustainability goal. Thus, it is unlikely that existing biotech firms indirectly suffer negative spillovers from new, lower-quality life sciences startups within the same VC portfolio. To further alleviate this concern, we test whether VC engagement intensity affects drug project discontinuation due to lack of funding or lower quality and find that it does not, as shown in Table 7.

Columns (3) and (4) present the second-stage results for drug development status with instrumented VC engagement intensity measures. Consistent with our baseline results in Table 5, the coefficients for size-based measures are positive and significant, while the coefficients for *HHI*-based measures are negative and significant. For comparison, their magnitudes are much greater than the corresponding OLS estimates. Jiang (2017) shows that it is common for IV estimates to be much larger than their OLS counterparts. This magnitude change in our paper is likely due to differences between local average treatment effects (LATE) captured by the state pension shocks in the 2SLS framework and average treatment effects (ATE) captured in the OLS regressions. We argue that our IV compilers are the VCs that have to respond to the sustainable investment requirement by shifting away from brown industries. This argument is also consistent with our weighting strategy in the IV construction: VCs with previously larger portfolio sizes and diversification are expected to reduce the scope of investments by a larger degree following the shock. We argue that these treated VCs tend to be generalists with investments spanning, for exam-

ple, both the energy and life sciences sectors. Following the shock, they would allocate additional oversight towards biotech firms, potentially diverting human capital that was previously used to monitor the energy sector. However, these new managers may lack the necessary expertise in the life sciences sector, leading to substantial intervention in project prioritization. As a result, we expect to observe a larger LATE among these compilers.

We interpret the above findings as evidence that engaging VCs may prematurely hold back most innovative projects for pipeline prioritization. To support this interpretation, we conduct several additional analyses. First, we examine heterogeneity by identifying projects that are likely to receive higher priority. Because primary market investors mainly value the performance of a startup's lead pipeline, VCs have strong incentives to focus on faster-progressing projects: a "winner-picking" tendency well documented in the life sciences industry by Robinson (2008). In Table IA.8, we split the sample by defining a project as "high-priority" if it is strictly more advanced than all other projects in the developer's pipeline. We find no evidence that VC engagement slows the progress of these high-priority projects. Instead, the coefficients in the "low-priority" group are nearly twice as large as our baseline estimates in Table 5, indicating that the holding-back effect is concentrated among lower-priority projects. These results also help address concerns about selection on unobserved startup quality. The existence of more advanced projects in a developer's pipeline signals higher technological potential and stronger human capital at the startup level. Therefore, a quality-based explanation would not predict the larger negative effects observed in the first two columns of Table IA.8.

Next, we examine the exit outcomes of the low-priority projects. Once a project becomes stagnant, startups can have multiple exit choices, including explicit termination, shelving, or out-licensing. In the case of shelving, the project is not officially discontin-

ued but becomes a "zombie project," with no further trial updates or announcements. In Table IA.9, we focus on stagnant projects, defined as those that remain in the same development phase for at least two years. Among these, 17.7 percent are shelved within the subsequent two years, while only 2.2 percent are formally terminated. None are explicitly out-licensed. The remaining projects either progress or continue to report clinical activity. We find that VC engagement is significantly associated with a higher likelihood of zombification among low-priority projects. Unfortunately, we cannot observe the underlying rationale behind these silent failures. On the other hand, although VC engagement does not significantly increase the overall likelihood of formal termination, likely due to the low frequency of such events, it does influence the stated reason for termination conditional on discontinuation. To be specific, the Cortellis database collects the reasons for drug indications that have ever experienced discontinuation and categorizes them into pipeline priority, lack of funding, and lack of efficacy, if possible. In our project sample, 252 initial projects were discontinued from 2000Q1 to 2020Q4. Lack of funding is the most common reason, accounting for 28% of all discontinuations, with lack of efficacy and pipeline priority contributing 12% and 15%, respectively. In total, around 55% of all the projects have explicit reasons, and we group the remaining projects into the "unknown reason" category.[12] We perform the following regression:

$$Reason_{i,j,k} = \alpha + \beta VC\ Engagement_k + \Phi X_k + FEs + \epsilon_{i,j,k} \tag{3}$$

Conditional on a project of drug j in indication i terminated by company k, $Reason$ indicates whether it is suspended for a particular reason. The focal regressors are defined

[12]In the regression sample, a few observations are dropped due to being singleton observations with fixed effects. The distribution is similar: lack of funding (28%), pipeline priority (14%), and lack of efficacy (13%).

similarly in Equation (2). Since each project only has one observation upon discontinuation, we are no longer working on a panel sample, constraining us from including the same set of fixed effects. Instead, we include the ICD-9 fixed effects to absorb the heterogeneity of research difficulty across different therapeutic categories, and the startup location fixed effects to absorb the impacts from R&D clusters. In the control variables, we include VC financing amounts and the number of indications targeted for the drug. The latter captures the degree of experimentation at the molecular level.

Table 7 columns (1) and (2) report the regression results for drugs discontinued due to pipeline priority. The outcome variable is one if the project is discontinued because the developing company wants to prioritize the development of other projects and zero otherwise. We find the coefficient estimates of both measures are negative and significant at the 1% level, suggesting that less active VCs are associated with fewer projects discontinued due to pipeline priority. Table 7 columns (3) – (6) present the regression results for drugs discontinued due to lack of funding or efficacy. We do not find any significant relation between engagement and lack of funding, suggesting that there exists no evidence that startups invested by smaller funds are financially constrained. Moreover, VC engagement intensity does not correlate with the lack of efficacy at all, suggesting that even professional investors have difficulty distinguishing project qualities. These null results help rule out the alternative interpretation that larger VCs contribute to drug project success by providing funding and they are better at screening projects. Overall, these results suggest that active VCs intervene in the drug development process mainly through project prioritization.

4.2 Economics of the conflicts

We further argue that VCs may prioritize projects that align with their own preferences, potentially hindering progress in certain therapeutic areas. Conflicting preferences between investors and founders can arise due to differences in investment horizons or concerns about portfolio cannibalization. Active VCs, by virtue of their greater attentiveness, are more likely to recognize and act on these conflicts. Moreover, the marginal benefit of avoiding costly investments or negative spillovers is higher for VCs with more concentrated portfolios. Consequently, we expect such conflicts to occur more frequently as VC engagement intensifies.

First, while the founding team aims to maximize the startup's value over their careers, VCs operate with a much shorter investment horizon due to the 10-year contractual structure. Without information asymmetry, this mismatch in horizon would not matter: Even if VCs exit earlier, they would be compensated based on the fairly discounted value of the startup. However, investments in innovative startups, particularly in the life sciences sector, feature substantial uncertainty and a high degree of information asymmetry. As outsider investors cannot distinguish between good and bad startups, they will impose an underpricing discount for high-quality projects in the pooling equilibrium (Akerlof, 1978). Consistent with this argument, Barrot (2017) shows that VC funds with a longer remaining horizon select younger companies at an earlier stage of their development. In Table 8, we conduct a similar analysis by splitting the sample based on the vintage of the investing funds. We hypothesize that the incentive to prioritize faster projects becomes more pronounced as a fund approaches its liquidation period. Supporting this hypothesis, we find significant negative effects of VC engagement on project progression only within the "old" fund subsample. In column (2), the coefficient on the HHI-based measure is three times

larger than that in the "young" fund subsample, and the coefficient in column (3) becomes indistinguishable from zero.

Thus, we hypothesize that VCs prefer projects that can generate publicly observable signals as soon as possible within a limited time horizon. This hypothesis implies that they would rationally hold back projects with *ex-ante* longer periods to progress. The logic is that VCs expect that the public progression signals are likely to arrive beyond the contractual window, exposing them to underpricing risks. We then sorted the sample into two sub-samples based on the average trial length for each drug indication (at the ICD-9 level). In particular, we leverage all drug development information from the Cortellis database and calculate the average quarters that it takes for all projects in each ICD-9 (clustering 3) level from the commencement to the completion of the Phase 3 clinical trial. We then code indications from ICD-9 classifications that have developing lengths below (above) the median as "fast (slow) ICD-9" indications. Table IA.10 reports the regression results for these two subsamples. As shown in column (3), the coefficients of the size-based measures are almost three times larger than those in the slow ICD-9 subsample (column 1).

The second conflict arises from the externalities within portfolio startups. From each startup's perspective, it hedges technology failure risks by exploring multiple indications using the focal molecule. This diversification, however, can negatively impact VC portfolio management by increasing the likelihood that two commonly-owned startups compete in the same disease areas. VCs want to avoid this internal competition for several reasons. First, the FDA awards market exclusivity to each newly approved drug, blocking similar technologies from entering the same therapeutic area for many years. Jointly investing in late-stage competitors can lead to duplicated R&D costs. Second, although competing

startups can use different technologies, their research progress can cannibalize each other's chances by raising the bar for FDA approval. As seen in the previous Acerta Pharma example, drug developers often need to demonstrate significant efficacy improvements over state-of-the-art technology. Therefore, the breakthrough of one portfolio company may increase the trial difficulty for others. Finally, even if all the competing projects can be approved, they will erode each other's potential market power. Consequently, while the startup values the continuation of additional projects, VCs may view them as diverting resources from the primary indication and potentially undermining portfolio value. Consistently, Li et al. (2023) document that after a portfolio drug progresses into Phase 2, VCs tend to redirect other portfolio startups' competing pipelines into different areas.

The implication of the second conflict is that active VCs may prefer each startup to focus on a primary therapeutic area. To test this hypothesis in Table 9, we first identify all additional projects within the same ICD category held by a focal project's VC investors. These projects can either belong to the focal project's own developer or to commonly-owned competing startups. We then normalize the number of projects in each group by the total number of (all-ICD) projects invested in by the VCs, creating the variables *Own Share* and *Competing Share*, respectively. To interpret our results, it is mostly straightforward to focus on the coefficients of HHI-based measures in Table 9. Column (2) suggests that startups held by more concentrated VCs tend to focus on a specific disease, as indicated by a higher fraction of projects developed by themselves in the same area. Conversely, VC engagement intensity is associated with a smaller fraction of competing projects from commonly-owned startups in column (4). The coefficients on size-based measures align with this interpretation.

4.3 Robustness checks

We perform a battery of robustness checks. We validate the findings by showing effects hold across the VC size distribution, confirming the engagement channel, using value-weighted or lead-VC measures, defining the concentration at industry and geographic measures, extracting investment data from an alternative database, and using an alternative measure of VC monitoring.

First, one concern is that our results may reflect the inherently lower, yet unobserved quality, of smaller or more specialized VCs, rather than the effects of their engagement. We address this concern in two ways. First, our instrumented results alleviate this issue: Figure IA.3 shows that VCs exposed to ESG pressures span the full size distribution, with a disproportionate share among larger firms. This reduces the likelihood that our findings are driven by lower-quality or financially constrained VCs that cater to state LPs due to limited access to alternative capital sources. Second, we partition the sample in multiple ways and show that relatively smaller or more focused VCs continue to slow innovation progress, even within projects backed by older VCs or those with IPO experience (Tables IA.11 to IA.13). For example, Table IA.13 reports similar coefficients on both size and concentration, regardless of whether the VC had previously incubated a successful life science IPO in our sample.

Second, we argue that the observed project prioritization is driven by active VC involvement. While our baseline results proxy engagement through VC size and specialization, we further examine a more direct outcome of such involvement: founder replacement. Motivated by the Acerta Pharma case and Fact 2, we conduct a subsample analysis using founder turnover as evidence of intervention. Table IA.14 shows that VC concentration is significantly associated with slower research progress, but only when the startup has

experienced changes in its founding team. These results suggest that we are not simply capturing unobserved preferences or management styles of small or specialized VCs. Rather, we uncover a concrete channel through which engagement can impact continuity in the executive team.

Third, in the previous results, we focus on the engagement by equally weighting all VC investors of the focal startup. The alternative empirical design is to utilize a value-weighted measure, where we implicitly assume that VCs with more recent investments have more control power. Table IA.15 shows that the results are consistent. One may argue that the five-year window is too short or that the investment weights do not proportionally capture the control power. We also only focus on the lead VC investors, as they arguably have the most significant control power to navigate the experimentation process. We benchmark our results using all the VCs as the Pitchbook data itself has substantial missing observations in the lead VC indicator, and we have to infer the lead status by cumulative investment amounts. Table IA.16 repeats the analyses focusing solely on the engagement of the lead VC investor. For any given quarter, the lead VC investor is defined as the one who has made the most investment in the startup over the past five years. Consistent with the results in Table 5, the positive coefficient of *Ln(Lead VC Size)* and the negative coefficient of *Lead VC HHI* suggest that a more active lead VC impedes the progress of clinical trials.

Fourth, one baseline measure of VC engagement intensity uses the concentration of allocation weights across individual firms. We construct the startup-level HHI measures as we focus on the VC engagement channel: even when VCs diversify within the life sciences sector by holding more biotech startups, the average intervention on each firm still tends to reduce. In Table IA.17, we confirm that our results hold with alternatively defining

concentration at the industry or headquarters location level.

Next, we test whether our results are robust to using alternative data sources. We recollect VC investment data from VentureXpert data, re-construct VC engagement intensity measures with VentureXpert deals, match Cortellis drug companies with VentureXpert investees, and replicate our baseline results. Table IA.18 reports the results for Equation (2) with VentureXpert data. We have slightly more observations when using VentureXpert data since VentureXpert might misclassify PE deals as VC deals. Nevertheless, all columns (1)-(4) are consistent with those in Table 5. Hence, our baseline findings are robust to the alternative VC data source (or, in other words, our baseline results are not driven by different coverage of VC deals).

Lastly, we interpret our main results through the channel that the VC engagement interferes with the strategic experimentation process. Our identification strategy utilizes the exogenous variations of VC portfolio construction due to LPs' investment policy. A related strategy is to follow Bernstein et al. (2016) and leverage the introduction of direct flights between the headquarters of drug companies and their lead VC investors as an exogenous shock for conducting on-site engagement. To do so, we identify nearby airports for each drug company and its lead VC investors by those located within 50 miles of driving distance from the headquarters city centers. We then collect monthly airline route data from the T-100 Domestic Segment Database from 2000 to 2020, maintained by the Bureau of Transportation Statistics (BTS), and construct a dummy variable to indicate the availability of direct flights between drug company k and its lead VC investors at quarter t. $Direct\,Flight_{k,t}$ equals one if there is at least one flight per week with at least 100 seats available between any pairs of company k's nearby airports and its lead VC's nearby airports by quarter t, and zero otherwise. Among the 1,397 unique drug companies in our

baseline sample, 257 experienced the introduction of new direct airlines originating from their lead VC investors from 2000 to 2020.

To evaluate the effects of VC engagement intensity on drug development progress, we employ the difference-in-difference (DiD) approach with the following regressions:

$$Next\,Phase_{i,j,k,p,t} = \alpha + \beta Direct\,Flight_{k,t} + \Phi X_{k,t} + \gamma_{i,j} + \delta_p + \zeta_t + \epsilon_{i,j,k,p,t}. \quad (4)$$

Equation (4) is almost the same as Equation (2), except that we replace the focal regressors with $Direct\,Flight_{k,t}$.[13] Given that $Direct\,Flight_{k,t}$ is time-variant and only turns on after a lead VC investor gets treated, β should be viewed as the DiD coefficient. Since OLS regressions with two-way fixed effects (TWFE method) similar to Equation (4) are the workhorse models for staggered adoption research designs, we first report our results using the TWFE method in columns (1), (3), and (5) of Table IA.19. Nevertheless, recent literature has shown that the estimates of such equations are consistent only with strong assumptions about homogeneity in treatment effects (Sun and Abraham, 2021; Baker et al., 2022). So we re-estimate the dynamic treatment effects with the interaction weighted (IW method) estimator proposed by Sun and Abraham (2021) and report the average treatment effects from IW estimators in columns (2), (4), and (6).

Columns (1) and (2) of Table IA.19 report the results based on Equation (4) in the full sample. The coefficient estimates of β are negative in both columns and statistically significant at a 5% significance level in column (2). Figure IA.4 plots the coefficient dynamics, exhibiting the absence of any pre-trends. These results suggest that increased lead-VC engagement likely slows down the strategic experimentation process following the direct

[13] We also add the control variable for the number of quarters since the first investment of the startup ("# Quarters since first inv") as Bernstein et al. (2016) have a similar variable to control for startup age.

flight introduction. We also split the full sample into early-stage and late-stage projects. We document negative effects in the early-stage subsample as shown by the negative and significant coefficients. On the other hand, the effect of VC monitoring on late-stage clinical trial progress, if anything, is mixed.

Our results do not necessarily contradict Bernstein et al. (2016), as only 5.6% of their sample companies are in the life sciences sector. Besides, drug companies frequently adopt an "evergreening" strategy, in which they patent small modifications of existing molecules to extend the potential market power of existing products (Hemphill and Sampat, 2012; Li et al., 2021). So, patents also reflect strategic marketing decisions in late-stage trials. We do find positive effects, though insignificant, after the treatment among Phase 2 and 3 projects in Figure IA.4. Overall, the analyses suggest the heterogeneous roles of VC oversight in R&D. Excessive engagement may lead to premature withholding of early-stage projects. However, more monitoring might be beneficial to the commercialization of late-stage projects.

4.4 Implications

What are the implications of our results? To begin with, it would be a misinterpretation to conclude that smaller or more specialized VCs are dominated in the life sciences sector from a fund return perspective. Although these VCs are associated with lower exit probabilities, their prioritization strategies increase conditional valuations. As a result, expected payoffs for these VCs are not necessarily low. Additionally, prioritization may enable VCs to better manage R&D costs and improve investment efficiency. To illustrate this point, Figure IA.5 plots the expected exit valuation ratio across startup bins sorted by investor size and concentration. For each startup, we calculate this ratio by normalizing the total

offering amount for IPOs, the deal amount for M&As, or zero (for non-exited startups) by the cumulative VC investment, adjusted to 2023 real dollars. We find no clear association between the expected exit valuation ratio and fund size or concentration, with the possible exception that extremely small VCs show slightly lower ratios.

This similarity in performance masks substantial heterogeneity in experimentation strategies driven by investor characteristics, with important implications for product-market outcomes across therapeutic areas. As discussed in Section 4.2, projects in different disease areas may be prioritized differently by VCs, depending on R&D difficulty and market competition. In Figure IA.6 Panel A, we explore this heterogeneity by repeating the analysis from Table 5 in subsamples across 11 broad therapeutic areas. We then plot the coefficients of the size and concentration measures, weighting each "bubble" by the number of projects in the corresponding area. VC engagement is positively associated with slower R&D progress in most areas. Exceptions include Hematology and Infectious Diseases, likely areas being prioritized.

However, Figure IA.6 Panel A does not imply that pipeline prioritization necessarily reduces the number of products ultimately approved. Prioritization may improve efficiency by reducing overcommitment to weak projects (Guenzel and Liu, 2023) and mitigating moral hazard in funding (Inderst et al., 2007). More broadly, VC engagement can support professionalization, fundraising, and recruitment (Hellmann and Puri, 2002; Bottazzi et al., 2008; Amornsiripanitch et al., 2019), all of which are valuable for late-stage commercialization. In Figure IA.6 Panel B, we explicitly test whether VC characteristics affect the likelihood of approval at the project level. We find strong evidence that pipeline prioritization influences approval outcomes in Psychiatry (a deprioritized area) and Hematology (a prioritized area). In other areas, the relationship between prioritization and approval is

weaker.

Table IA.20 focuses on a particularly relevant therapeutic area for pipeline prioritization: oncology. This area is characterized by high failure risks, which creates strong incentives for founders to hedge by pursuing multiple projects simultaneously. Oncology trials are also lengthy by nature, and the area accounts for the largest number of projects in our sample, implying intense competition and potential cannibalization across projects. We find that VC engagement significantly slows innovation progress and reduces the number of ultimately approved products in this domain. These findings suggest that traditional VCs may operate within a constrained investment spectrum, both in terms of development stage and therapeutic focus. As a result, expanding VC-style funding alone may be insufficient to close broader financing and therapeutic gaps in the sector. A recent survey of life science founders and investors conducted by the European Investment Bank underscores this concern. Respondents emphasized the need for novel financing mechanisms that would support "a higher number of projects," "increased funding per project," "longer-term, patient capital," and "neglected therapeutic areas."[14] These demands reflect the constraints associated with VC-driven prioritization strategies and highlight the need for complementary funding models. The emergence of more patient capital, such as impact funds, royalty financing, and megafunds, may help fill the gaps left by traditional VC financing. Despite concerns that their scale and long horizons may weaken monitoring, their presence remains important to support underfunded experimentation.

[14] See Exhibit 27 in *Financing the Next Wave of Medical Breakthroughs: What Works and What Needs Fixing?*, European Investment Bank, March 2018. Respondents answered the question: "What objective should a novel financing mechanism achieve? Please tick all that apply."

5 Conclusion

This paper highlights the heterogeneity in the real effects of VC engagement on startup experimentation. By utilizing granular data from the life sciences sector, we explore an understudied aspect of VC engagement in startups' strategic experimentation processes: project prioritization. We document that startups backed by smaller or more concentrated VCs, while being more engaged, drive early-stage pipeline prioritization, which affects both the timing and direction of innovation outcomes.

Rather than uniformly accelerating or impeding innovation in all areas, prioritization introduces trade-offs: it can generate more advanced lead pipelines and higher payoffs per successful exit, while also increasing the overall startup failure rate. These effects vary across therapeutic areas, with some fields, such as oncology, suffering more from focused investor attention than others. Our results suggest that investor characteristics systematically shape the direction of innovation and highlight the importance of aligning startup needs with the structure and strategy of their investors.

We interpret these patterns as evidence of inherent conflicts of interest between traditional VC investors and founders during the strategic experimentation process. Despite being a crucial player in the startup ecosystem, our findings point to the limitations of the traditional VC model in supporting higher-risk, longer-horizon innovation. In this context, the emergence of more patient capital, such as impact funds, royalty-based vehicles, and life sciences megafunds, offers a valuable complement to existing financing models.

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Table 1: Summary statistics

This table reports the summary statistics of project quarterly data in our sample from 2000Q1 to 2020Q4. The unit of observation is a drug-indication×year-quarter combination. The number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile of the following variables are reported: *Next Phase* is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise; *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *Ln(VW-Size)* is the natural logarithm of the investment-amount-weighted mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *VW-HHI* is the investment-amount-weighted mean of the HHI index for a drug company's investing VCs; *VC Amount* is the aggregated investment amount for a drug company's VC investors in the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The project development status data are collected from Cortellis. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. The VC investment data used to construct VC engagement measures are collected from Pitchbook.

	Obs.	Mean	STD	p25	p50	p75
Next Phase	77,874	0.013	0.113	0.000	0.000	0.000
Size	77,874	38.358	39.076	13.000	28.750	49.273
Ln(Size)	77,874	3.157	1.122	2.565	3.359	3.897
VW-Size	77,874	40.424	42.908	13.000	30.000	51.936
Ln(VW-Size)	77,874	3.181	1.149	2.565	3.401	3.950
HHI	77,874	0.227	0.218	0.072	0.149	0.303
VW-HHI	77,874	0.220	0.220	0.068	0.138	0.287
VC Amount (in millions)	77,874	35.737	50.540	6.923	20.289	48.586
Ln(VC Amount)	77,874	16.567	1.535	15.750	16.826	17.699
# Developing Drugs	77,874	6.979	6.086	3.000	5.000	9.000

Table 2: Pipeline summary statistics of life science IPOs

This table reports the pipeline summary statistics of drug companies exiting via IPOs from 2000Q1 to 2020Q4. The unit of observation is a drug company. The number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile of the following variables are reported: *# Projects Ever* is the number of projects that a drug company has ever initiated over the sample period; *# Projects Active Upon IPO* is the number of active projects of a drug company upon its IPO; *# Pre-clinical Projects Upon IPO* is the number of projects in the pre-clinical stage of a drug company upon its IPO; *# Phase-1 Projects Upon IPO* is the number of projects in Phase 1 of a drug company upon its IPO; *# Phase-2 Projects Upon IPO* is the number of projects in Phase 2 of a drug company upon its IPO; *# Phase-3 Projects Upon IPO* is the number of projects in Phase 3 of a drug company upon its IPO; *% Projects Suspended before IPO* is the percentage of projects suspended by a drug company prior to its IPO; *% Pre-clinical Projects Upon IPO* is the percentage of active projects in the pre-clinical stage of a drug company upon its IPO; *% Phase-1 Projects Upon IPO* is the percentage of active projects in Phase 1 of a drug company upon its IPO; *% Phase-2 Projects Upon IPO* is the percentage of active projects in Phase 2 of a drug company upon its IPO; *% Phase-3 Projects Upon IPO* is the percentage of active projects in Phase 3 of a drug company upon its IPO. The project development status data are sourced from Cortellis. The VC investment data used to construct VC engagement intensity measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum.

	Obs.	Mean	STD	p25	Median	p75
# Projects Ever	258	11.783	10.185	5.000	8.000	15.000
# Projects Active Upon IPO	258	7.275	6.577	3.000	5.000	10.000
# Preclinical Projects Upon IPO	258	4.791	4.496	2.000	4.000	7.000
# Phase-1 Projects Upon IPO	258	1.287	2.951	0.000	0.000	1.000
# Phase-2 Projects Upon IPO	258	1.043	2.366	0.000	0.000	1.000
# Phase-3 Projects Upon IPO	258	0.155	0.506	0.000	0.000	0.000
% Projects Suspended before IPO	258	33.907	25.905	9.091	33.333	52.500
% Preclinical Projects Upon IPO	258	67.119	33.244	50.000	75.000	100.000
% Phase-1 Projects Upon IPO	258	13.364	20.772	0.000	0.000	23.077
% Phase-2 Projects Upon IPO	258	14.996	25.086	0.000	0.000	23.077
% Phase-3 Projects Upon IPO	258	4.521	17.134	0.000	0.000	0.000

Table 3: VC engagement and startup governance

This table shows the results of Equation (1) with Cortellis drug companies from 2000Q1 to 2020Q4. The unit of observation is a drug company $\times$ year-quarter combination. The dependent variable in columns (1) and (2) is *New board*, which is a dummy variable equal to one if the drug company has any new board members from its VC investors in a given quarter, and zero otherwise. The dependent variable in columns (3) and (4) is *# Turnover*, which is the number of founding team turnovers for a company in a given quarter; we focus on the following founding positions: founder, chief executive officer, chief technology officer, chief marketing officer, chief operating officer, president, chairman, and owner. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures and board entrance indicators are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include company and year-quarter fixed effects. Standard errors are double clustered at the company and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	New Board		*# Turnovers*	
	(1)	(2)	(3)	(4)
Ln(Size)	-0.012***		-0.006*	
	(-2.79)		(-1.73)	
HHI		0.070***		0.040*
		(3.80)		(1.94)
Ln(VC Amount)	0.014***	0.013***	0.004	0.003
	(5.22)	(4.77)	(1.66)	(1.40)
# Developing Drugs	-0.001	-0.001	0.002	0.002
	(-0.84)	(-0.95)	(1.42)	(1.39)
Company FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.1086	0.1090	0.0969	0.0970
Number of observations	18,107	18,107	18,107	18,107

Table 4: VC engagement and life science startup M&A/IPO exits

This table shows the relationship between investor engagement and life science startup exits via IPOs and M&As from 2000Q1 to 2020Q4. As a cross-sectional analysis, the unit of observation is a drug company. The dependent variable in columns (1) and (2) is *IPO*, which is a dummy variable equal to one if the drug company exits via IPOs within the sample period, and zero otherwise. The dependent variable in columns (3) and (4) is *M&A*, which is a dummy variable equal to one if the drug company exits via M&As within the sample period, and zero otherwise. The dependent variable in columns (5) and (6) is *IPO/M&A*, which is a dummy variable equal to one if the drug company exits via an IPO or an M&A within the sample period, and zero otherwise. Columns (1) and (2) include the non-exiting and IPO-exiting firms. Columns (3) and (4) include the non-exiting and M&A-exiting firms. The last two columns include both exiting and non-exiting firms. For the simple mean of a drug company's investing VC portfolio sizes (*Size*), we first take the time-series average across the sample period of a focal company. We then take the natural logarithm to generate *Ln(Size)*. The equal-weighted HHI index, *HHI*, is also averaged across the sample period of a focal company. *Ln(Avg VC Amount)* is the natural logarithm of the average investment amount received by a drug company over the sample period. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include ICD-9, drug company founding year, and startup headquarters fixed effects. Standard errors are double clustered at the ICD-9 and drug company headquarter level; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	IPO		*M&A*		*IPO/M&A*	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Size)	0.039***		0.035***		0.043***	
	(2.69)		(2.75)		(2.94)	
HHI		-0.154**		-0.145**		-0.183**
		(-2.49)		(-1.99)		(-2.44)
Ln(Avg VC Amount)	0.103***	0.108***	0.047***	0.051***	0.100***	0.105***
	(6.37)	(6.78)	(3.60)	(3.99)	(6.85)	(7.26)
ICD-9 FE	Yes	Yes	Yes	Yes	Yes	Yes
Startup HQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4649	0.4629	0.3174	0.3156	0.3944	0.3926
Number of observations	968	968	898	898	1,143	1,143

Table 5: VC engagement and innovation progress

This table shows the results of Equation (2) using Cortellis drug development data from 2000Q1 to 2020Q4. The unit of observation is a drug-indication × year-quarter combination. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	(1)	(2)	(3)	(4)
Ln(Size)	0.006***	0.005***		
	(3.11)	(2.71)		
HHI			-0.037***	-0.037***
			(-3.87)	(-3.86)
Ln(VC Amount)		0.003***		0.004***
		(2.86)		(3.36)
# Developing Drugs		-0.001		-0.001
		(-1.60)		(-1.40)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2274	0.2276	0.2276	0.2279
Number of observations	77,173	77,173	77,173	77,173

Table 6: Instrumented VC engagement and innovation progress

This table shows the 2SLS results of Equation (2) using an instrument based on LPs' ESG investment preference. The unit of observation is a drug-indication×year-quarter combination. *Exposure-Size* is the fraction of a focal drug company's pre-shock VC investors exposed to sustainability-oriented LPs, weighted by each VC's size prior to the shock. *Exposure-Div* is the fraction of a focal drug company's pre-shock VC investors exposed to sustainability-oriented LPs, weighted by each VC's diversification *(1 - HHI)* prior to the shock. Columns (1) and (2) report the first-stage regression results for the VC engagement measures in Table 5: *Ln(Size)* and *HHI*. Columns (3) and (4) report the second-stage regression results using two instrumented VC engagement measures. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years. *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Ln(Size)	*HHI*	*Next Phase*	
	(1)	(2)	(3)	(4)
Exposure-Size	-0.712***			
	(-5.80)			
Exposure-HHI		0.064***		
		(4.04)		
$\widehat{Ln(Size)}$			0.034**	
			(2.53)	
$\widehat{HHI}$				-0.392***
				(-2.69)
Ln(VC Amount)	0.081***	0.005	0.001	0.005***
	(5.30)	(1.61)	(0.41)	(3.20)
# Developing Drugs	-0.011**	0.004***	-0.000	0.001
	(-2.35)	(4.25)	(-0.78)	(1.16)
Drug Indication FE	Yes	Yes	Yes	Yes
Phase FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Kleibergen-Paap F-test	33.68	16.32	–	–
R^2	0.025	0.008	–	–
Observations	77,173	77,173	77,173	77,173

Table 7: VC engagement and project discontinuation

This table shows the results of Equation (3) with a subsample of discontinued projects from 2000Q1 to 2020Q4. The unit of observation is a drug indication. The dependent variable in columns (1) and (2) is *Pipeline Priority*, which is a dummy variable equal to one if the drug indication is discontinued due to pipeline priority, and zero otherwise. The dependent variable in columns (3) and (4) is *Lack of Funding*, which is a dummy variable equal to one if the drug indication is discontinued due to lack of funding, and zero otherwise. The dependent variable in columns (5) and (6) is *Lack of Efficacy*, which is a dummy variable equal to one if the drug indication is discontinued due to lack of efficacy, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Indications* is the natural logarithm of one plus the number of indications under active development at a focal drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include ICD-9, and headquarters fixed effects. Standard errors are double clustered at the ICD-9 and drug company headquarters levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Pipeline Priority		*Lack of Funding*		*Lack of Efficacy*	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Size)	-0.191***		0.035		0.033	
	(-3.11)		(0.59)		(0.79)	
HHI		1.371***		0.643		-0.387
		(3.39)		(1.15)		(-1.55)
Ln(VC Amount)	-0.016	-0.079	0.130	0.165**	0.061	0.068
	(-0.26)	(-1.38)	(1.57)	(2.12)	(1.27)	(1.58)
# Indications	-0.157**	-0.111	0.082	0.041	0.190***	0.188***
	(-2.12)	(-1.39)	(0.56)	(0.28)	(4.06)	(4.33)
ICD-9 FE	Yes	Yes	Yes	Yes	Yes	Yes
Startup HQ FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.6836	0.6904	0.6595	0.6676	0.7013	0.7054
Number of observations	163	163	163	163	163	163

Table 8: VC engagement and innovation progress: heterogeneity due to fund age

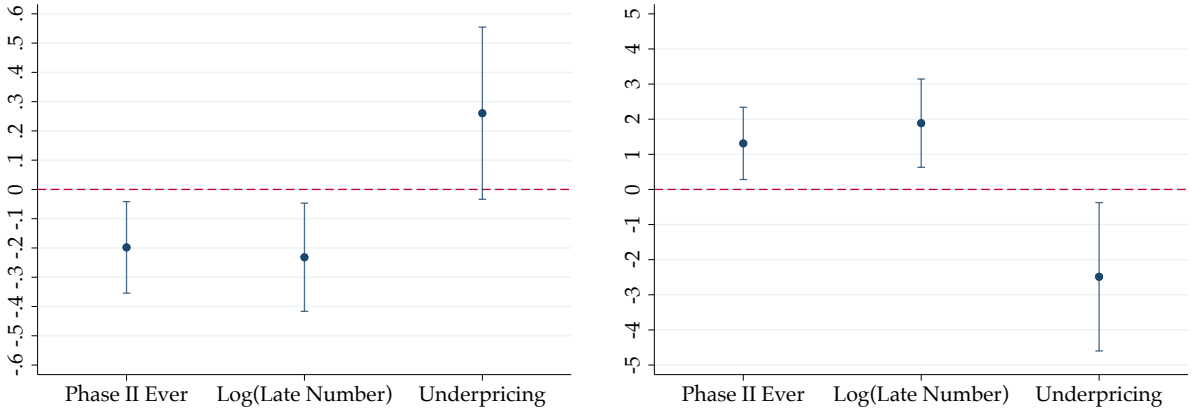
This table shows the results of Equation (2) in subsamples split by investors' fund age. The unit of observation is a drug-indication×year-quarter combination. We follow Barrot (2017) and define the threshold of an "old" fund as at least three years. Columns (1) and (2) report the results using drug indications whose developing companies received at least one investment from a fund that was more than three years old at the time of investment. Columns (3) and (4) report the results using drug indications whose developing companies received investments only from funds that were less than three years old at the time of investment. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	Fund Age ≥3		*Fund Age <3*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.010***		0.000	
	(2.94)		(0.03)	
HHI		-0.048***		-0.016
		(-2.79)		(-1.16)
Ln(VC Amount)	0.005***	0.006***	0.001	0.001
	(3.20)	(3.73)	(0.46)	(0.41)
# Developing Drugs	-0.000	-0.000	-0.001	-0.001
	(-0.59)	(-0.57)	(-1.59)	(-1.54)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2640	0.2642	0.2422	0.2422
Number of observations	48,569	48,569	27,805	27,805

Table 9: VC engagement and therapeutic area concentration

This table shows the relationship between VC engagement and startup therapeutic area concentration. The unit of observation is a drug-indication $\times$ year-quarter combination. For each focal project, *Own Share* is the fraction of other projects developed by its firm in the same ICD area over all the projects held by its VC investors. *Competitor Share* is the fraction of other projects developed by other commonly-owned startups in the same ICD area over all the projects held by its VC investors. A commonly-owned startup is another startup also backed by the focal startup's VC investors. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	Own Share		*Competitor Share*	
	(1)	(2)	(3)	(4)
Ln(Size)	-0.016***		0.005**	
	(-3.16)		(2.57)	
HHI		0.062***		-0.025**
		(4.06)		(-2.34)
Ln(VC Amount)	0.001	-0.001	0.000	0.001
	(0.55)	(-0.23)	(0.57)	(1.30)
# Developing Drugs	0.003***	0.003***	-0.000	-0.000
	(3.63)	(3.46)	(-1.33)	(-1.28)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.8732	0.8731	0.8370	0.8372
Number of observations	77,173	77,173	77,173	77,173



(a) Coefficients of *Ln(Size)*

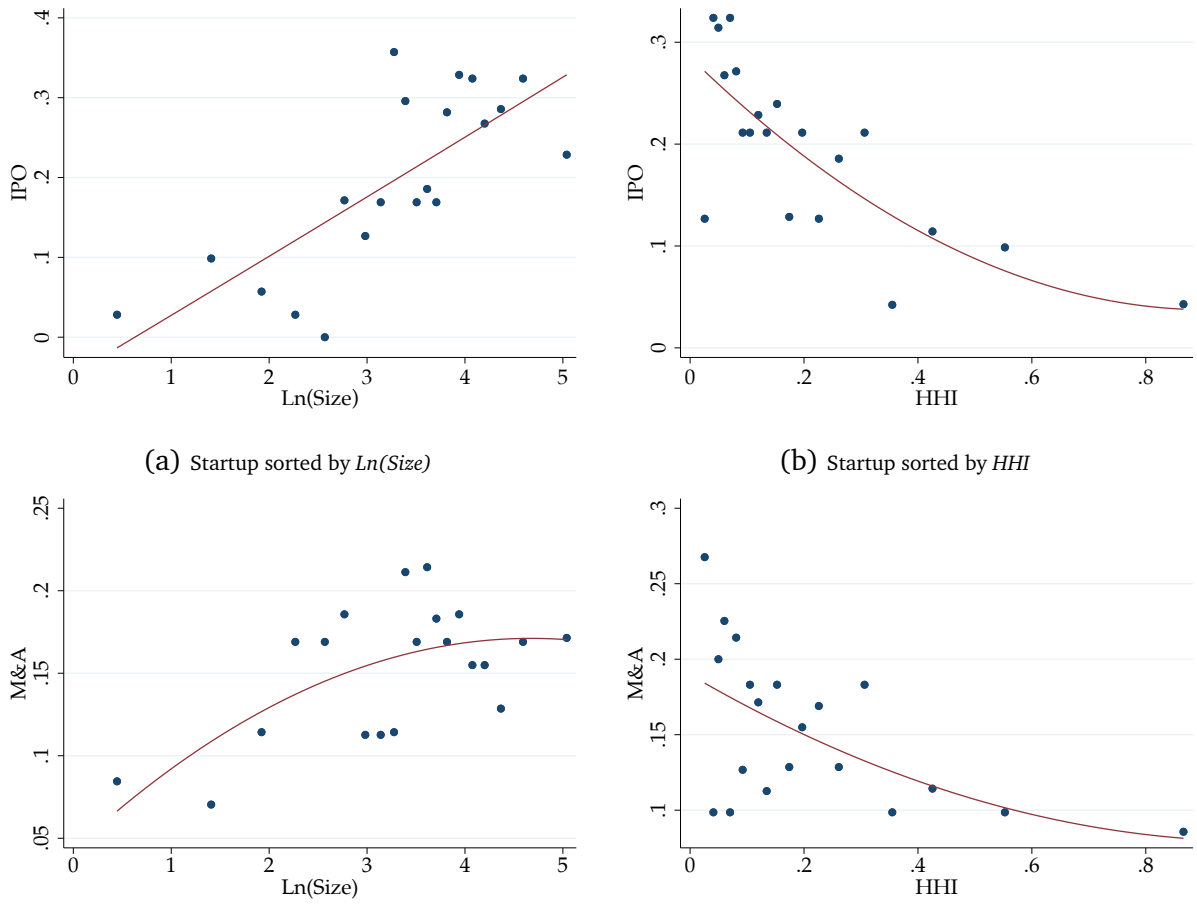
(b) Coefficients of *HHI*

Figure 1: **VC engagement and IPO performance**

Figure 1 shows the relationship between VC engagement and life-science startup IPO performance from 2000Q1 to 2020Q4. Each figure plots the coefficients of *VC Engagement* (i.e., β) by estimating the following regression:

$$Performance_i = \alpha + \beta VC\ Engagement_i + \epsilon_i,$$

where outcome variables *Performance* are: (i) an indicator for whether the startup has at least one project in Phase II or later, (ii) the logarithm of (one plus) Phase II and later projects, and (iii) IPO underpricing, defined as *(Offer Price - 1stDay Close Price)/1stDay Close Price*. Figures 1a and 1b measure VC engagement intensity with *Ln(Size)* and *HHI*, respectively. For each IPO i, we take the average of VC engagement measures across the startup's pre-IPO quarters. The error bars denote 95% confidence intervals. Standard errors are clustered at the startup's leading ICD-9 and headquarters levels.



(a) Startup sorted by *Ln(Size)*

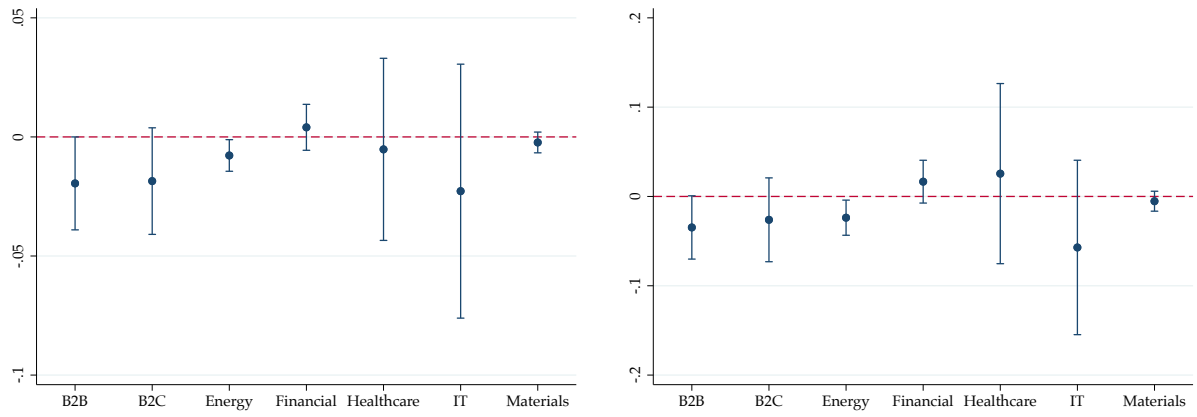
(b) Startup sorted by *HHI*

(c) Startup sorted by *Ln(Size)*

(d) Startup sorted by *HHI*

Figure 2: **VC engagement and life science startup exit outcomes**

Figure 2 shows the relationship between VC engagement and life-science startup exit probability from 2000Q1 to 2020Q4. In each figure, all startups are sorted into 20 equal-size bins with similar levels of VC engagement intensity over the sample period. Figures 2c and 2d measure VC engagement intensity with *Ln(Size)* and *HHI*, respectively. The y-axis indicates the fraction of startups that exit via IPO or M&A within each bin. The red curve in each figure plots the fitted quadratic regression of VC engagement on exit outcomes. The project development status data are sourced from Cortellis. The VC investment data used to construct VC engagement intensity measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum.



(a) Total number of companies within an industry

(b) Total amount of real dollar within an industry

Figure 3: **LP sustainability goals and VC investment strategies**

Figure 3 shows the relationship between industry-level investment strategies and the adoption of sustainability investment goals by VCs' limited partners within a 10-year window around the shock. Each figure plots the coefficients on *Treated* (i.e., β) by estimating the following regression for VC investment in industries of *Business Products and Services (B2B)*, *Consumer Products and Services (B2C)*, *Energy*, *Financial Services (Financial)*, *Healthcare*, *Information Technology (IT)* and *Materials and Resources (Materials)*:

$$VC\ Investment_{j,t} = \alpha + \beta Treated_{j,t} + FE + \epsilon_{j,t}.$$

Figures 3a and 3b measure VC investment with *Ln(number of companies)*, and *Ln(amount of real dollar)*, respectively. *Treated* is a dummy variable equal to one after the VC's LP adopts sustainability investment goals by year t, and zero otherwise. Investor fixed effects and year-quarter fixed effects are included. The error bars denote 95% confidence intervals. The VC investment data are collected from Pitchbook. The GDP price deflator data used to deflate the VC investment amount over time are sourced from the U.S. Federal Reserve.

Internet Appendix to "How Does VC Engagement Direct Startup Experimentation?"

Table IA.1: Summary statistics by R&D stages

This table replicates the summary statistics of Table 1 by splitting the sample into early and late stages. Panel A reports the statistics for projects in the pre-clinical phase or Phase 1, and Panel B reports the statistics for projects in Phase 2 or Phase 3. All other details are the same as in Table 1.

	Obs.	Mean	STD	p25	Median	p75
Panel A: Pre-clinical Phase & Phase 1						
Next Phase	67,015	0.014	0.117	0.000	0.000	0.000
Size	67,015	38.711	38.428	14.000	29.000	50.000
Ln(Size)	67,015	3.179	1.107	2.639	3.367	3.912
VW-Size	67,015	40.791	42.046	13.601	30.317	52.952
Ln(VW-Size)	67,015	3.206	1.133	2.610	3.412	3.969
HHI	67,015	0.223	0.215	0.071	0.147	0.297
VW-HHI	67,015	0.216	0.216	0.067	0.135	0.283
VC Amount (in millions)	67,015	35.356	50.496	6.576	19.714	48.200
Ln(VC Amount)	67,015	16.527	1.569	15.699	16.797	17.691
# Developing Drugs	67,015	7.025	6.098	3.000	5.000	9.000
Panel B: Phase 2 & Phase 3						
Next Phase	10,859	0.007	0.084	0.000	0.000	0.000
Size	10,859	36.177	42.797	9.667	27.000	46.000
Ln(Size)	10,859	3.020	1.197	2.269	3.296	3.829
VW-Size	10,859	38.158	47.827	9.667	27.000	46.750
Ln(VW-Size)	10,859	3.028	1.232	2.269	3.296	3.845
HHI	10,859	0.249	0.235	0.077	0.163	0.348
VW-HHI	10,859	0.246	0.243	0.073	0.151	0.327
VC Amount (in millions)	10,859	38.084	50.747	8.486	25.000	50.250
Ln(VC Amount)	10,859	16.813	1.279	15.954	17.034	17.733
# Developing Drugs	10,859	6.694	6.005	3.000	5.000	9.000

Table IA.2: VC engagement and startup governance: robustness of value-weighted measures

This table shows the results of Equation (1) with Cortellis drug companies from 2000Q1 to 2020Q4. The unit of observation is a drug company $\times$ year-quarter combination. The dependent variable in columns (1) and (2) is *New board*, which is a dummy variable equal to one if the drug company has any new board members from its VC investors in a given quarter, and zero otherwise. The dependent variable in columns (3) and (4) is *# Turnovers*, which is the number of founding team turnovers for a company in a given quarter; we focus on the following founding positions: founder, chief executive officer, chief technology officer, chief marketing officer, chief operating officer, president, chairman, and owner. *Ln(VW-Size)* is the natural logarithm of the investment-amount-weighted mean of a drug company's investing VC portfolio sizes; *VW-HHI* is the investment-amount-weighted mean of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures and board entrance indicators are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include company and year-quarter fixed effects. Standard errors are double clustered at the company and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	New Board		*# Turnovers*	
	(1)	(2)	(3)	(4)
Ln(VW-Size)	-0.012***		-0.009**	
	(-2.79)		(-2.12)	
VW-HHI		0.069***		0.048**
		(3.69)		(2.25)
Ln(VC Amount)	0.014***	0.013***	0.005*	0.004
	(5.22)	(4.81)	(1.84)	(1.50)
# Developing Drugs	-0.001	-0.001	0.002	0.002
	(-0.89)	(-1.00)	(1.36)	(1.33)
Company FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.1086	0.1090	0.0970	0.0972
Number of observations	18,107	18,107	18,107	18,107

Table IA.3: VC engagement and innovation progress: robustness of standard errors clustered at the company and ICD-chapter level

This table shows the results of Equation (2) using Cortellis drug development data from 2000Q1 to 2020Q4. The details are the same as in Table 5, except that standard errors in columns (1) - (2) are double clustered at the company and year-quarter levels, and standard errors in columns (3) - (4) are double clustered at the ICD-chapter and year-quarter levels. All columns include phase, drug-indication, and year-quarter fixed effects. t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	(1)	(2)	(3)	(4)
Ln(Size)	0.005**		0.005***	
	(2.00)		(2.76)	
HHI		-0.037***		-0.037***
		(-2.75)		(-4.12)
Ln(VC Amount)	0.003***	0.004***	0.003***	0.004***
	(2.84)	(3.42)	(2.84)	(3.38)
# Developing Drugs	-0.001	-0.001	-0.001	-0.001
	(-1.45)	(-1.28)	(-1.57)	(-1.40)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Cluster	Company	Company	ICD-chapter	ICD-chapter
R^2	0.2276	0.2279	0.2276	0.2279
Number of observations	77,173	77,173	77,173	77,173

Table IA.4: Repeated interactions of state pension LPs and VCs

This table shows the results of whether a VC's State Pension LPs change their funding behavior after adopting sustainability investment goals. The unit of observation is a VC-fund-LP combination. We only include the VCs (and their state pension LPs) that have invested in our sample startups, and there is only one observation for each LP committing to a given VC fund (i.e., multiple commitments to one fund from the same LP are collapsed and included only once). We exclude VCs that have raised only one fund from any LP during the sample period. In column (1), *Future Commit* equals one if the LP has committed funding to this VC's any future funds, and zero otherwise. In column (2), *Next Commit* equals one if the LP has committed funding to this VC's next fund, and zero otherwise. *Treated* is one if the state pension LP has adopted the ESG goal by year t, and zero otherwise. All columns include the LP-VC pair fixed effects and the fund initiation year fixed effects. The means of the outcome variables are also reported. Standard errors are double clustered at the investor and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Future Commit	*Next Commit*
	(1)	(2)
Treated	-0.021	-0.147
	(-0.17)	(-1.18)
LP-VC Pair FE	Yes	Yes
Fund Year FE	Yes	Yes
R^2	0.5237	0.4802
Number of Observations	1,309	1,309
Y Mean	0.705	0.457

Table IA.5: LP sustainability goals and VC investment strategies

This table shows how VCs change investment strategies after their LPs have adopted sustainability investment goals. The unit of observation is a VC investor $\times$ year-quarter combination. We only include the sample VCs that have invested in our sample startups. In columns (1) and (3), *#Com* is the natural logarithm of the total number of new companies that a VC has invested in a given industry in a given quarter; in columns (2) and (4), *Amt* is the logarithmic amount of real dollar (in 2023 USD) to new companies that a VC has invested in a given industry in a given quarter. *Treated* is a dummy variable equal to one after the VC's LP adopts sustainability investment goals by year t, and zero otherwise. Columns (1) - (2), and (3) - (4) report the results for VC investment in the energy and health sector, respectively. The VC investment data are collected from Pitchbook. The GDP price deflator data used to deflate VC investment amount over time are sourced from the U.S. Federal Reserve. All columns include investor fixed effects and year-quarter fixed effects. Standard errors are double clustered at the investor and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Energy		*Healthcare*	
	# Com	*Amt*	*# Com*	*Amt*
	(1)	(2)	(3)	(4)
Treated	-0.008**	-0.024**	-0.005	0.026
	(-2.30)	(-2.37)	(-0.27)	(0.50)
Investor FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.1645	0.1591	0.3063	0.3108
Number of observations	118,795	118,795	118,795	118,795

Table IA.6: LP sustainability goals and startup founder turnovers

This table shows the results of Equation (1) using an instrument based on LPs' ESG investment preference. The unit of observation is a drug company × year-quarter combination. *Exposure-Size* is the fraction of a focal drug company's pre-shock VC investors exposed to sustainability-oriented LPs, weighted by each VC's size prior to the shock. *Exposure-Div* is the fraction of a focal drug company's pre-shock VC investors exposed to sustainability-oriented LPs, weighted by each VC's diversification (1 - HHI) prior to the shock. The dependent variable is *# Turnover*, which is the number of founding team turnovers for a company in a given quarter; we focus on the following founding positions: founder, chief executive officer, chief technology officer, chief marketing officer, chief operating officer, president, chairman, and owner. *Ln(VC Amount)* is the logarithmic aggregated investment amount made by all VC investors to the drug company in the past five years; *# Developing Drugs* denotes the number of drugs under active development from a drug company. The VC investment data to construct VC activism measures and board entrance indicators is collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include company and year-quarter fixed effects. Standard errors are double clustered at company and year-quarter level; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	# Turnovers	
	(1)	(2)
Exposure-Size	0.044**	
	(2.34)	
Exposure-Div		0.045**
		(2.33)
Ln(VC Amount)	0.004	0.004
	(1.45)	(1.45)
# Developing Drugs	0.002	0.002
	(1.51)	(1.51)
Company FE	Yes	Yes
Year-Quarter FE	Yes	Yes
R^2	0.0968	0.0968
Number of observations	18,107	18,107

Table IA.7: Testing the instrument's effects on biotech funding raising

This table shows the null results of the instrument on biotech fundraising using Pitchbook data from 2000Q1 to 2020Q4. The unit of observation is a company $\times$ year-quarter combination. The dependent variable is *Amount*, which is the amount of real dollar (in 2023 USD) follow-up funding raised by the startup each year. *Treated* equals one if this startup's VCs have been affected by the ESG sustainability shock, and zero otherwise. *Exposure-Size* is the fraction of a focal drug company's pre-shock VC investors exposed to sustainability-oriented LPs, weighted by each VC's size prior to the shock. *Lagged cumulative amount* is the cumulative real dollars raised by the startup by year $t-1$; *Lagged round number* is the number of financing rounds for the startup by year $t-1$; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. All columns include company and investment year-quarter fixed effects. Standard errors are double clustered at the company and year-quarter levels; t statistics are in parentheses; $^{*}p<0.1,^{**}p<0.05,^{***}p<0.01$.

	Total Amount	
	(1)	(2)
Treated	0.495	
	(0.65)	
Exposure-Size		-0.991
		(-0.56)
Lagged cumulative amount	-0.081*	-0.080*
	(-1.94)	(-1.92)
Lagged around number	-1.134**	-1.138**
	(-2.16)	(-2.16)
# Developing Drugs	0.054	0.055
	(1.05)	(1.07)
Company FE	Yes	Yes
Year-Quarter FE	Yes	Yes
R^2	0.1382	0.1382
Number of observations	19,760	19,760

Table IA.8: Priority pressure and innovation progress

This table shows the effects of prioritization incentives on drug innovation process using Cortellis drug development data from 2000Q1 to 2020Q4. The unit of observation is a drug-indication $\times$ year-quarter combination. Columns (1) and (2) report the results using drug indications that are not at the most advanced development stage within their developing company; columns (3) and (4) report the results using drug indications that are at the most advanced development stage within their developing company. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	Low-priority		*High-priority*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.010***		-0.002	
	(3.24)		(-0.68)	
HHI		-0.051***		-0.007
		(-3.35)		(-0.57)
Ln(VC Amount)	0.003**	0.004***	0.004**	0.004*
	(2.24)	(3.10)	(2.13)	(1.94)
# Developing Drugs	0.000	0.001	-0.002**	-0.002**
	(0.77)	(1.13)	(-2.49)	(-2.37)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2627	0.2629	0.2157	0.2157
Number of observations	36,298	36,298	40,438	40,438

Table IA.9: VC engagement and exit outcomes for stagnant projects

This table shows the relationship between VC engagement and drug indication exit outcomes using Cortellis drug indications that have ever remained in the same phase (stagnant) for at least eight consecutive quarters during the period from 2000Q1 to 2020Q4. The unit of observation is a drug indication. The dependent variable in columns (1) and (2) is *Terminated*, which is a dummy variable equal to one if the drug indication is explicitly documented as discontinued or suspended within eight quarters since stagnancy, and zero otherwise. The dependent variable in columns (3) and (4) is *Zombie*, which is a dummy variable equal to one if the drug indication is explicitly documented as having no development progress within eight quarters since stagnancy, and zero otherwise. The dependent variable in columns (5) and (6) is *Pipeline Exits*, which is a dummy variable equal to one if the drug indication is explicitly documented as discontinued or suspended or having no development progress within eight quarters since stagnancy, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple mean of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures and board entrance indicators are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include company and year-quarter fixed effects. Standard errors are double clustered at the company and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Terminated		*Zombie*		*Pipeline Exits*	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Size)	-0.001		-0.016*		-0.016*	
	(-0.30)		(-1.85)		(-1.82)	
HHI		-0.001		0.076*		0.073*
		(-0.10)		(1.93)		(1.84)
Ln(VC Amount)	0.007***	0.007***	0.030***	0.029***	0.033***	0.031***
	(4.07)	(3.93)	(4.53)	(4.66)	(4.74)	(4.84)
# Developing Drugs	-0.001	-0.001	-0.000	-0.000	-0.001	-0.000
	(-1.22)	(-1.19)	(-0.13)	(-0.10)	(-0.25)	(-0.21)
Phase FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1044	0.1043	0.0990	0.0989	0.1012	0.1009
Number of observations	3,158	3,158	3,745	3,745	3,805	3,805

Table IA.10: VC engagement and innovation progress: heterogeneity due to experimentation length

This table shows the results of Equation (2) for subsamples split by experimentation length. The unit of observation is a drug-indication×year-quarter combination. Columns (1) and (2) report the results using drug indications from ICD-9 classifications that have below-median developing lengths; columns (3) and (4) report the results using drug indications from ICD-9 classifications that have above-median developing lengths. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Next Phase			
	Fast ICD-9 Indications		*Slow ICD-9 Indications*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.003		0.008***	
	(1.10)		(2.70)	
HHI		-0.030***		-0.045***
		(-2.96)		(-3.08)
Ln(VC Amount)	0.003**	0.004**	0.003*	0.004**
	(2.37)	(2.59)	(1.81)	(2.32)
# Developing Drugs	-0.000	-0.000	-0.001*	-0.001
	(-0.61)	(-0.48)	(-1.74)	(-1.49)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2170	0.2172	0.2419	0.2422
Number of observations	38,638	38,638	38,535	38,535

Table IA.11: VC engagement and innovation progress: robustness of VC seniority

This table shows the results of Equation (2) in subsamples split by VC seniority. The unit of observation is a drug-indication $\times$ year-quarter combination. Columns (1) and (2) report the results using drug indications that have ever been invested in by old VCs; columns (3) and (4) report the results using drug indications from companies that have never been invested in by old VCs; We define old VCs as investors that are more than 30 years old at the time of investment. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Next Phase			
	Ever backed by old VCs		*Never backed by old VCs*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.007**		0.005*	
	(2.39)		(1.71)	
HHI		-0.038***		-0.037**
		(-3.08)		(-2.49)
Ln(VC Amount)	0.004**	0.004***	0.003*	0.003**
	(2.61)	(3.11)	(1.70)	(2.05)
# Developing Drugs	-0.001	-0.001	-0.001	-0.000
	(-0.73)	(-0.73)	(-1.15)	(-0.88)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2076	0.2077	0.2485	0.2489
Number of observations	32,918	32,918	44,255	44,255

Table IA.12: VC engagement and innovation progress: robustness of VC IPO experience

This table shows the results of Equation (2) for subsamples split by VC IPO experience. The unit of observation is a drug-indication $\times$ year-quarter combination. Columns (1) and (2) report the results using drug indications that have ever been invested in by VCs with IPO experience; columns (3) and (4) report the results using drug indications from companies that have never been invested in by VCs with IPO experience. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	Ever backed by VCs with IPOs		*Never backed by VCs with IPOs*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.005*		0.006*	
	(1.74)		(1.67)	
HHI		-0.026**		-0.042**
		(-2.35)		(-2.43)
Ln(VC Amount)	0.003**	0.004***	0.002	0.003
	(2.41)	(2.69)	(0.85)	(1.24)
# Developing Drugs	-0.001***	-0.001***	0.001	0.001
	(-3.36)	(-3.30)	(0.78)	(0.95)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.1946	0.1947	0.2811	0.2817
Number of observations	42,965	42,965	34,208	34,208

Table IA.13: VC engagement and innovation progress: robustness of VC life science IPO experience

This table shows the results of Equation (2) for subsamples split by VC life science IPO experience. The unit of observation is a drug-indication $\times$ year-quarter combination. Columns (1) and (2) report the results for drug indications that have ever been invested in by VCs with life science IPO experience; columns (3) and (4) report the results for drug indications from companies that have never been invested in by VCs with life science IPO experience. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

	Next Phase			
	Ever backed by VCs with IPOs		*Never backed by VCs with IPOs*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.009*		0.005**	
	(1.72)		(2.03)	
HHI		-0.044**		-0.035***
		(-2.04)		(-3.35)
Ln(VC Amount)	0.006	0.008**	0.003**	0.003***
	(1.65)	(2.05)	(2.43)	(2.85)
# Developing Drugs	-0.001**	-0.001**	-0.001	-0.000
	(-2.12)	(-2.00)	(-0.93)	(-0.83)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2103	0.2104	0.2316	0.2319
Number of observations	8,547	8,547	68,626	68,626

Table IA.14: VC engagement and startup governance: heterogeneity due to founder turnovers

This table shows the results of Equation (2) for subsamples split by founder turnovers. The unit of observation is a drug-indication×year-quarter combination. Columns (1) and (2) report the results using drug indications from startups that have ever experienced founder turnovers from 2000Q1 to 2020Q4; columns (3) and (4) report the results using drug indications from startups that have never experienced founder turnovers from 2000Q1 to 2020Q4. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Ever Has Founder Turnover		*Never Has Founder Turnover*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.008**		0.003	
	(2.16)		(0.90)	
HHI		-0.060***		-0.016
		(-3.14)		(-1.63)
Ln(VC Amount)	0.003**	0.004***	0.003	0.003
	(2.28)	(3.03)	(1.60)	(1.66)
# Developing Drugs	-0.001	-0.001	-0.001	-0.001
	(-1.29)	(-1.39)	(-1.43)	(-1.32)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2225	0.2234	0.2360	0.2360
Number of observations	31,347	31,347	45,826	45,826

Table IA.15: VC engagement and innovation progress: robustness of value-weighted measures

This table shows the results of Equation (2) using Cortellis drug development data from 2000Q1 to 2020Q4. The unit of observation is a drug-indication $\times$ year-quarter combination. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(VW-Size)* is the natural logarithm of the investment-amount-weighted mean of a drug company's investing VC portfolio sizes; *VW-HHI* is the investment-amount-weighted mean of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. The VC investment data used to construct VC engagement measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are double clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase			
	(1)	(2)	(3)	(4)
Ln(VW-Size)	0.008***	0.007***		
	(3.91)	(3.44)		
VW-HHI			-0.037***	-0.036***
			(-4.32)	(-4.19)
Ln(VC Amount)		0.003***		0.003***
		(2.69)		(3.22)
# Developing Drugs		-0.001		-0.001
		(-1.46)		(-1.29)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2275	0.2277	0.2277	0.2279
Number of observations	77,173	77,173	77,173	77,173

Table IA.16: Lead VC engagement and innovation progress

This table shows the results of Equation (2) with lead VC engagement. The unit of observation is a drug-indication×year-quarter combination. The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Ln(Lead VC Size)* is the natural logarithm of a drug company's lead VC's portfolio sizes; *Lead VC HHI* is the the HHI index for a drug company's lead VC's portfolio; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company. A drug company's lead VC in a given quarter is defined as the VC investor who has made the most investment in the company over the past five years. The VC investment data used to construct VC engagement intensity measures are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Next Phase	
	(1)	(2)
Ln(Lead VC Size)	0.005***	
	(3.31)	
Lead VC HHI		-0.026***
		(-3.59)
Ln(VC Amount)	0.003***	0.003***
	(2.95)	(2.95)
# Developing Drugs	-0.001	-0.001
	(-1.55)	(-1.47)
Phase FE	Yes	Yes
Drug Indication FE	Yes	Yes
Year-Quarter FE	Yes	Yes
R^2	0.2277	0.2278
Number of observations	77,173	77,173

Table IA.17: VC engagement and innovation progress: robustness of alternative concentration measures

This table shows the results of Equation (2) using Cortellis drug development data from 2000Q1 to 2020Q4. The details are the same as in Table 5, except that VC engagement intensity measures are constructed at the portfolio company industry level in columns (1) - (2) and at the portfolio company headquarters state level in columns (3) - (4). All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

	Next Phase			
	Industry Concentration		*Geographic Concentration*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.012***		0.010***	
	(3.98)		(3.81)	
HHI		-0.028***		-0.031***
		(-3.30)		(-2.89)
Ln(VC Amount)	0.003***	0.004***	0.003***	0.003***
	(3.16)	(3.64)	(2.88)	(2.96)
# Developing Drugs	-0.001	-0.001	-0.001	-0.001*
	(-1.53)	(-1.42)	(-1.55)	(-1.70)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2278	0.2277	0.2277	0.2277
Number of observations	77,173	77,173	77,173	77,173

Table IA.18: VC engagement and innovation progress using VentureXpert data

This table shows the results of Equation (2) using the VentureXpert data. The details are the same as in Table 5, except that the VC investment data used to construct VC engagement intensity measures are collected from VentureXpert. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are clustered at the ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Next Phase			
	(1)	(2)	(3)	(4)
Ln(Size)	0.004**			
	(2.34)			
Ln(VW-Size)		0.004***		
		(2.66)		
HHI			-0.020**	
			(-2.55)	
VW-HHI				-0.016**
				(-2.55)
Ln(VC Amount)	0.003***	0.003***	0.003***	0.003***
	(2.86)	(2.90)	(3.11)	(3.11)
# Developing Drugs	-0.001**	-0.001**	-0.001**	-0.001**
	(-2.18)	(-2.14)	(-2.17)	(-2.16)
Phase FE	Yes	Yes	Yes	Yes
Drug Indication FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R^2	0.2048	0.2048	0.2048	0.2048
Number of observations	91,908	91,908	91,908	91,908

Table IA.19: Flight-induced VC engagement and innovation progress

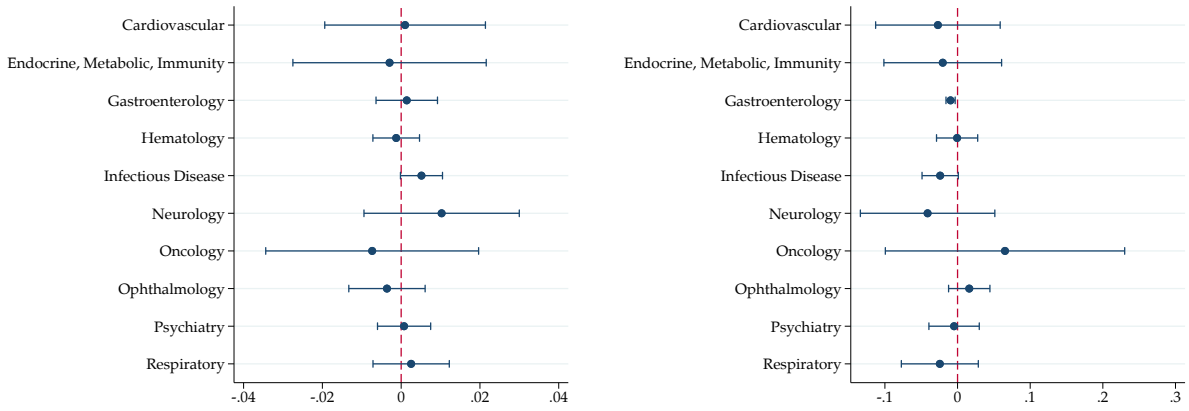
This table shows the results of Equation (4) using Cortellis drug development data from 2000Q1 to 2020Q4. The unit of observation is a drug-indication×year-quarter combination. Columns (1) and (2) report the full sample results; columns (3) and (4) report the results using pre-clinical and Phase 1 projects; columns (5) and (6) report the results using Phase 2 and Phase 3 projects. Columns (1), (3), (5) use the OLS estimator; Columns (2), (4), (6) report the post-treatment average IW estimators proposed by Sun and Abraham (2021). The dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise. *Lead VC-treated* is a dummy variable equal to one if direct flights between a drug company's headquarters and its lead VC's headquarters have become available by quarter t; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company in the past five years; *# Developing Drugs* is the number of drugs under active development at the drug company in a given quarter; *# Quarters since first inv* is the number of quarters since the first investment made by a drug startup's lead investor. The US airline route data used to construct *Lead VC-treated* are collected from T-100 Domestic Segments data maintained by the Bureau of Transportation Statistics. All columns include phase, drug-indication, and year-quarter fixed effects. Standard errors are clustered at ICD-9 and year-quarter levels; t statistics are in parentheses; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Next Phase					
	All Phases		*Preclinical & Phase 1*		*Phase 2 & Phase 3*	
	(1)	(2)	(3)	(4)	(5)	(6)
Lead VC-treated	-0.008**	-0.010**	-0.011***	-0.017***	0.001	0.004
	(-2.12)	(-2.69)	(-3.03)	(-7.65)	(0.11)	(0.68)
Ln(VC Amount)						
# Developing drugs	-0.001		-0.000		-0.002**	
	(-1.65)		(-0.81)		(-2.23)	
# Quarters since first inv	0.000		0.000		0.001*	
	(1.37)		(0.64)		(1.95)	
Ln(VC Amount)	0.004***		0.003***		0.009**	
	(3.51)		(3.51)		(2.52)	
Drug Indication FE	Yes	Yes	Yes	Yes	Yes	Yes
Phase FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2275	0.2273	0.2337	0.2335	0.2219	0.2195
Number of observations	77,173	77,173	66,312	66,312	10,753	10,753

Table IA.20: VC engagement and innovation outcome: robustness in the case of Oncology

This table shows the relationship between VC engagement and innovation outcome, using data from Oncology projects only. In columns (1) and (2), the unit of observation is a drug company $\times$ year-quarter combination; the dependent variable is *Next Phase*, which is a dummy variable equal to one if the drug indication is going to progress to the next phase in the following quarter, and zero otherwise; *Ln(Size)* is the natural logarithm of the simple mean of a drug company's investing VC portfolio sizes; *HHI* is the simple average of the HHI index for a drug company's investing VCs; *Ln(VC Amount)* is the natural logarithm of the aggregated investment amount made by all VC investors in the drug company over the past five years; *# Developing Drugs* denotes the number of drugs under active development at a drug company; both columns include company and year-quarter fixed effects; standard errors are double clustered at the company and year-quarter levels. In columns (3) and (4), the unit of observation is a drug-indication project; the dependent variable is *Approved*, which is a dummy variable equal to one if the project ultimately receives approval from FDA; *Mean Ln(Size)* is the mean value of a project's *Ln(Size)* over its sample period; *Mean HHI* is the mean value of a project's *HHI* over its sample period; both columns include first year-quarter and ICD-9 fixed effects; standard errors are clustered at the company level. The VC investment data used to construct VC engagement measures and board entrance indicators are collected from Pitchbook. The IPO dates for drug companies are sourced from SDC Platinum and supplemented by Jay Ritter's IPO data. The M&A dates for drug companies are sourced from SDC Platinum. t statistics are in parentheses; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Next Phase		*Approved*	
	(1)	(2)	(3)	(4)
Ln(Size)	0.007***			
	(3.60)			
HHI		-0.025***		
		(-2.68)		
Mean Ln(Size)			0.001*	
			(1.76)	
Mean HHI				-0.010**
				(-2.39)
Ln(VC Amount)	0.002	0.003		
	(1.25)	(1.60)		
# Developing Drugs	-0.000	-0.000		
	(-0.44)	(-0.25)		
Phase FE	Yes	Yes	-	-
Drug Indication FE	Yes	Yes	-	-
Year-Quarter FE	Yes	Yes	-	-
ICD-9 FE	-	-	Yes	Yes
First Quarter FE	-	-	Yes	Yes
R^2	0.2789	0.2788	0.1568	0.1577
Number of observations	23,607	23,607	2,539	2,539



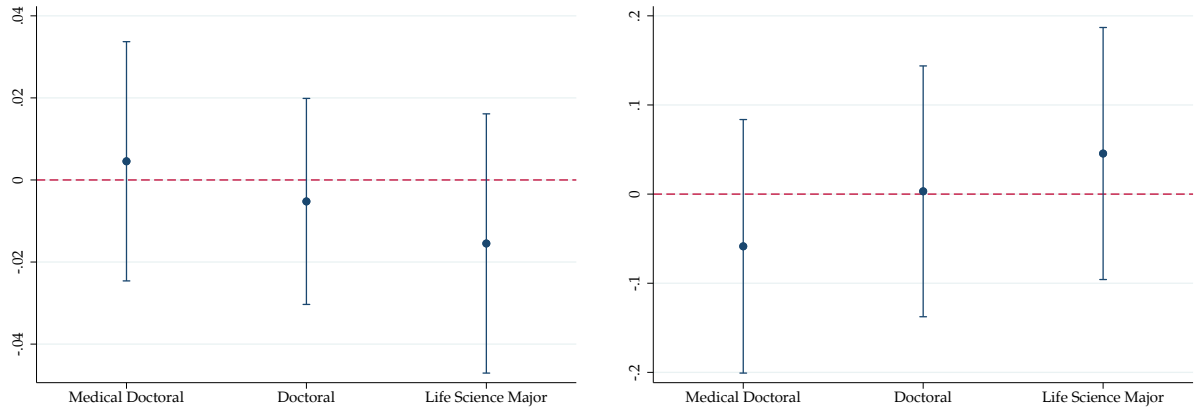
(a) Coefficients of *Ln(Size)* (b) Coefficients of *HHI*

Figure IA.1: **VC engagement and drug project disease areas**

Figure IA.1 shows the relationship between VC engagement intensity and drug-indication project disease areas from 2000Q1 to 2020Q4. Each figure plots the coefficients of *VC Engagement* (i.e., β) by estimating the following regression:

$$Disease\ Area_k^i = \alpha + \beta VC\ Engagement_k + \Phi X_k + FEs + \epsilon_k^i,$$

where the dependent variables *Disease Area* are the indicators on whether the startup has worked on disease areas of *Cardiovascular*, *Endocrine, Metabolic, and Immunity*, *Gastroenterology*, *Hematology*, *Infectious Disease*, *Neurology*, *Oncology*, *Ophthalmology*, *Psychiatry* and *Respiratory*, respectively. Figures IA.1a and IA.1b measure VC engagement intensity with *Ln(Size)* and *HHI*, respectively. The error bars denote 95% confidence intervals. The disease areas are classified as per ICD-9. The project development status data are sourced from Cortellis. The VC investment data used to construct VC engagement intensity measures are collected from Pitchbook.



(a) Coefficients of *Ln(Size)* (b) Coefficients of *HHI*

Figure IA.2: **VC engagement and founder educational background**

Figure IA.2 shows the relation between VC engagement intensity and founder educational background from 2000Q1 to 2020Q4. Each figure plots the coefficients of *VC Engagement* (i.e., β) by estimating the following regression:

$$Educational\ Background_k^i = \alpha + \beta VC\ Engagement_k + \Phi X_k + FEs + \epsilon_k^i,$$

where the dependent variables *Educational Background* are the number of founders with educational backgrounds of medical doctoral degree (*Medical Doctoral*), any doctoral degree (*Doctoral*), and life science majors (*Life Science Major*), respectively. Figures IA.2a and IA.2b measure VC engagement intensity with *Ln(Size)* and *HHI*, respectively. The error bars denote 95% confidence intervals. The project development status data are sourced from Cortellis. The VC investment data used to construct VC engagement intensity measures and founder profile data used to construct educational background measures are collected from Pitchbook.

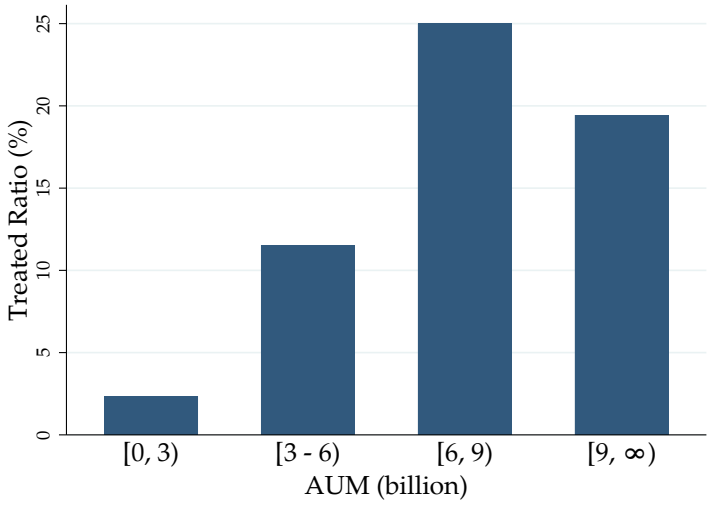


Figure IA.3: **Percentage of treated VCs by size**

Figure IA.3 illustrates the percentage of venture capital firms (VCs) that have been exposed to LPs' sustainability goals, categorized by assets under management (AUM) from 2000Q1 to 2020Q4. For each AUM category, this ratio is calculated by dividing the number of VCs with sustainability exposure by the total number of VCs in that category. All VC AUM data are sourced from Pitchbook.

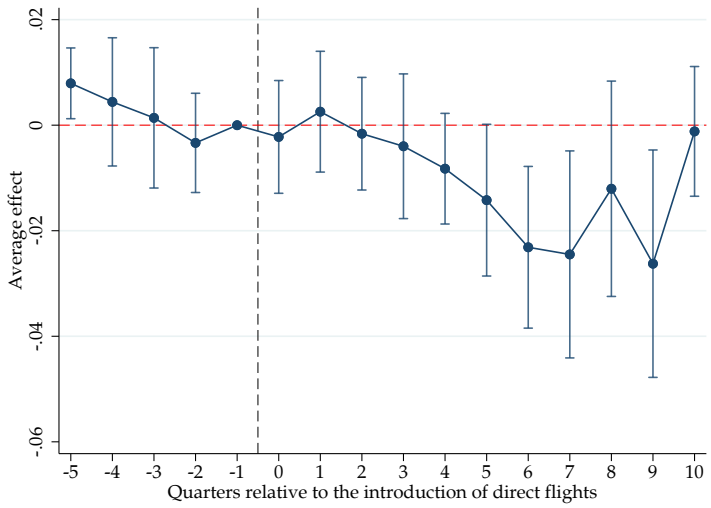
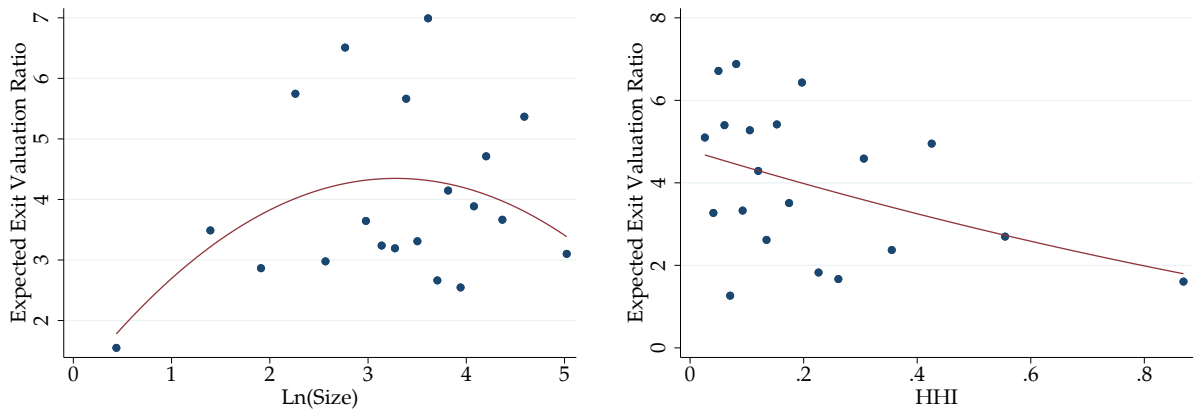


Figure IA.4: **Impacts of direct flights on drug development progress**

Figure IA.4 shows the event-study plots of the following equation using IW estimators proposed by Sun and Abraham (2021):

$$Next\,Phase_{i,j,k,p,t} = \alpha + \sum_{s=-5}^{10} \beta_s D_{s(k,t)} + \Phi X_{k,t} + \gamma_{i,j} + \delta_p + \zeta_t + \epsilon_{i,j,k,p,t}.$$

The dependent variable is $Next\,Phase_{i,j,k,p,t}$, which is a dummy variable equal to one if indication i of drug j at phase p from company k enters the next phase at time $t+1$. The key independent variable $D_{s(kt)}$ is a collection of indicator variables equal to one if for drug company k at time t, the introduction of a direct flight between k and its lead investor is s quarters away. The drug development progress data are collected from Cortellis. The US domestic direct flight data used to construct treatment dummies are collected from the T-100 Domestic Segments dataset. Both figures include phase, drug-indication, and year-quarter fixed effects. The bars represent 95 percent confidence intervals. Standard errors are double clustered at the drug company and year-quarter levels.

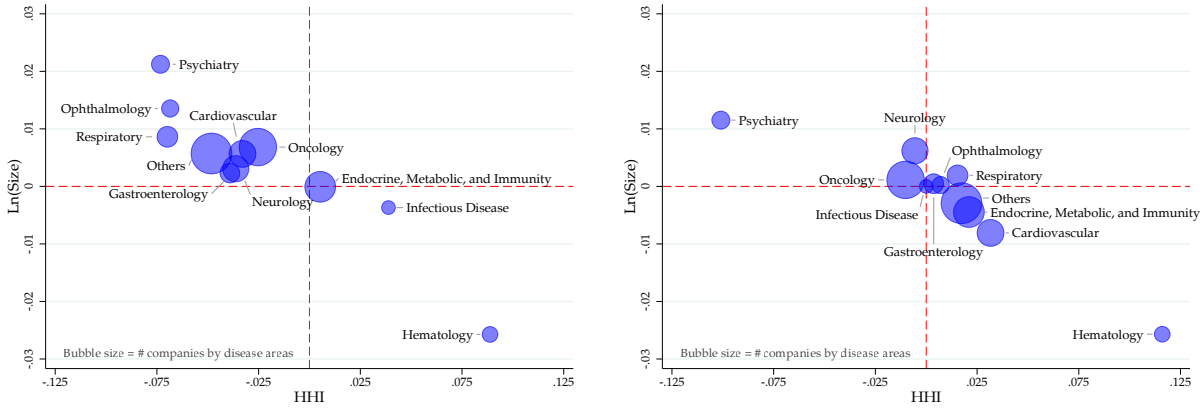


(a) Startup sorted by *Ln(Size)*

(b) Startup sorted by *HHI*

Figure IA.5: **VC engagement and startup exit valuation ratio**

Figure IA.5 shows the relationship between VC engagement and life science startup exit valuation ratios from 2000Q1 to 2020Q4. In each panel, startups are sorted into 20 equal-sized bins based on similar levels of VC engagement intensity over the sample period. Figures IA.5a and IA.5b measure engagement using *Ln(Size)* and *HHI*, respectively. The y-axis plots the mean exit valuation ratio within each bin. Exit valuation is defined as the total offering amount for IPOs, the deal amount for M&As, or zero for non-exited startups. The exit valuation ratio normalizes exit valuation by the cumulative VC investment for each startup. All dollar values are converted to 2023 real dollars. The red curve in each panel shows a fitted quadratic regression of VC engagement on the exit valuation ratio. Project development status data are sourced from Cortellis, VC investment data from PitchBook, and IPO/M&A valuation data for drug companies from SDC Platinum.



(a) Innovation progress by disease areas

(b) Approval likelihood by disease areas

Figure IA.6: **Drug innovation progress and approval likelihood by disease areas**

Figure IA.6 shows the relationship between VC engagement intensity and drug progressing and approval across disease areas from 2000Q1 to 2020Q4. Figure IA.6a plots the coefficients of VC engagement (i.e., β) by estimating the following regression for each disease area:

$$Next\ Phase_{i,j,k,p,t} = \alpha + \beta VC\ Engagement_{k,t} + FE + \epsilon_{i,j,k,p,t},$$

where the dependent variable is $Next\ Phase_{i,j,k,p,t}$, which is a dummy variable equal to one if indication i of drug j at phase p from company k enters the next phase at time $t+1$. Figure IA.6b plots the coefficients of VC engagement (i.e., β) by estimating the following regression for each disease area:

$$Approved_j = \alpha + \beta VC\ Engagement_j + FE + \epsilon_j.$$

In Figure IA.6b we take the average of VC engagement measures across projects within the same disease area; the outcome variable $Approval_j$ is a dummy variable equal to one if the given project ultimately receives approval from the FDA, and zero otherwise. The disease areas are classified as per ICD-9 and include Cardiovascular, Endocrine, Metabolic, and Immunity, Gastroenterology, Hematology, Infectious Disease, Neurology, Oncology, Ophthalmology, Psychiatry, Respiratory, and Others. The project development status data are sourced from Cortellis. The VC investment data used to construct VC engagement intensity measures are collected from Pitchbook. Each bubble size is weighed by the total number of projects in our sample.