The Impact of VC Financing on Entrepreneurial Experimentation: Evidence from Clinical Trials*

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Abstract

Startups rely heavily on experiments to generate data about the value of their product. In doing so, they must choose between less rigorous tests that might simply confirm prior optimism about a startup's potential or more rigorous (but costly) tests that might provide a more precise signal of its underlying potential. Building on recent theory in bayesian entrepreneurship, we argue that the rigor of early experimentation depends on a startup's funding status. A startup's experiments are likely to be more rigorous when they are influenced by external funders who might be more skeptical of a startup's success as compared to when no external funders are involved. We predict that this effect on experimental rigor is itself shaped by product novelty, competition and funder specialization. We examine these predictions in the biopharmaceutical industry, where startups can choose between more vs. less rigorous clinical trials to assess product safety and efficacy. Leveraging detailed data on the rigor of clinical trials and a difference-in-difference strategy, we show that startups conduct more rigorous trials with VC funding that without. This difference in rigor is larger for more novel ideas, in less competitive environments and for specialized funders. Our results speak to the endogenous nature of startup experimentation as a function of external stakeholders and the role of startup funding in shaping the design of experiments.

JEL Classifications: O31, I18, G24, L26

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1 Introduction

Entrepreneurship is a process of experimentation. Startups might begin with an initial hypothesis, but significant uncertainty must be resolved through costly experiments before their vision can be realized. For example, a founder might start based on an assumption about the viability of a certain technology or a critical customer need. But until costly investments such as customer interviews, market and technology research and prototyping are conducted, these assumptions remain on untested. A recent literature has theoretically examined how entrepreneurs design these experiments, highlighting the endogenous nature of startup testing and the impact of the testing regime on performance. For example, startups are more likely to be successful when entrepreneurs engage in a more "scientific" and hypothesis-driven experimentation process (Kerr et al., 2014; Camuffo et al., 2024).

A prominent feature of the endogeneity of startup experimentation is that the quality and quantity of tests can vary substantially across firms and markets. On one hand, startups must invest in many costly, high-quality tests to convince external stakeholders such as investors or regulators about their product's value. On the other hand, startups are usually quite confident about the value of their product and might not want to invest in costly and time consuming tests. In such cases, they might prefer to run fewer, less rigorous tests that satisfy basic requirements rather than waste costly resources on rigorous tests. For example, a biotech startup developing a new cancer treatment might choose between conducting a small, uncontrolled trial versus multiple large, randomized controlled trials that rigorously compares the new treatment to existing therapies. The startup could potentially prefer the less rigorous approach to accelerate time to market and reduce costs, especially when founders already believe strongly in their product's efficacy. One key insight then is that startups might not always choose the most rigorous testing regime. The quantity and quality of tests will depend crucially on the need to establish ground truth with skeptical stakeholders balanced against the cost of additional rigor in the testing regime.

One important implication is that as startups grow and bring on external investors, these stakeholders might have a direct impact on the nature of entrepreneurial experimentation. Insofar as external investors are more skeptical about a startup as compared to the founder, they might want

to increase the scrutiny the startup faces in terms of its early experiments. The result would a greater number of tests as well as an increase in the rigor of the tests that the startup choose. To return to our example, the biotech startup developing a cancer treatment might face pressure from VCs to conduct the large, randomized controlled trial despite the founders' initial preference for a quicker, less rigorous approach—because investors need stronger evidence to justify continued funding in such a high-risk, high-stakes environment. This would allow the VCs to "fail early and fail fast" before they sink further investment in the firm.

Moreover, the need for rigor when investors are involved might vary significantly with contextual factors. In particular, the increase in rigor might be a function of (a) the startup's technology, (b) the competitive enviroment and (c) investor background. Investors might be particularly skeptical when startups are working on particularly novel technology, when no other firms are pursuing the same idea or when investors have significant experience in the heathcare industry. In these cases, we expect funders to be particularly motivated to demand more rigorous testing as compared to the founding team alone. Despite the plausibility of this theory, no part work, either in the literature on entrepreneurial experimentation or entrepreneurial finance has tackled these questions. This is the challenge we tackle in this paper.

Specifically, we make progress on these questions by examining the impact of external funding events on the rigor of clinical testing by biopharmaceutical startups developing new drugs. While entrepreneurial testing (and its rigor) is typically unobservable, in this context, startup success depends on demonstrating the safety and efficacy of their product in a series of increasingly complex clinical trials. This means that clinical trials are high-stakes testing events that are central to a startups journey through the entrepreneurial process. Further, even though the Food and Drug Administration (FDA) has some guidelines on clinical trial design, startups often have significant leeway. For example, randomization of patients to treatment and control arms is considered the "gold standard." However, 55 percent of trials used to support drug approvals are not randomized and are still deemed valid by the FDA (Kaplan et al., 2023). Moreover, transparency regulations mandate the public reporting of clinical trials, which we utilize to track startups' clinical trial investments (U.S. Congress, 1997, 2007). These data not only report whether or not clinical trials were conducted but also provide information on their design (such as randomization and the use of

an appropriate control arm). We can use this information to evaluate the rigor in a consistent and unbiased way across startups and funding regimes to evaluate our research question.

In particular, we construct a dataset of 1,843 startups gathered from Pitchbook. To identify these startups, we focus on the set of U.S. pharmaceutical and biotechnology firms with early-stage (i.e., pre-venture or venture capital) funding. For each startup, we identify the date and amount of its initial VC funding. To characterize each startups' clinical trial investments, we incorporate clinical trial data from Cortellis Clinical Trials Intelligence. With this data, we are able to observe, for each trial, information about its sponsor, the year in which it was initiated, and the diseases it investigates. As a proxy for trial rigor, we also collect data on whether the trial was randomized, blinded, and included a comparator. With this data, we construct a startup-year panel, tracking each startup from its founding year to 2022. Rather than compare across startups with and without funders, we compare startups before and after funding events to make sure that we are comparing similar scientific ideas under different funding regimes. Specifically, we examine how VC funding shapes startups' clinical testing decisions using a difference-in-differences design with startup and year fixed effects, leveraging variation across startups and over time in the timing of their receipt of VC funding.

We find that startups have a greater number of trials and more rigorous trials when they are funded as compared to when they are not. Estimates suggest that VC funding significantly increase their likelihood of investing in a clinical trial by 96 percent. Supporting a causal interpretation of our results, event study analyses confirm minimal changes in investment activity prior to the funding event. Notably, in response to VC funding, startups are significantly more likely to increase investment in more rigorous trials, i.e., those that are randomized, blinded, and use a comparator, relative to less rigorous trials. Our findings of an increase in the rigor of entrepreneurial testing are consistent with the view that VCs may encourage startups to engage in more rigorous experimentation to quickly identify and terminate nonviable projects, thus reducing the time and resources on efforts unlikely to succeed in the long run. A whole host of additional analyses help rule out alternative explanations related to capital constraints or changing regulatory expectations around the timing of when a startup raises funds.

If our proposed mechanism is at play and VC funding influences trial design due to investors'

beliefs about a project's likelihood of success, then we would expect this effect to be moderated by factors that affect VCs' priors stated before including (a) product novelty (b) competition, and (c) funder specialization. Our empirical results suggest that VC funding increases the rigor of clinical trials precisely when investors are likely to be most skeptical about a startup's prospects: the increase in rigor following VC investment is greater for more novel products, stronger in less competitive disease areas, and more pronounced when VCs specialize in the biopharmaceutical sector.

Overall, our paper contributes to the emerging literature on the endogeneity of entrepreneural experimentation. This work has argued for an investigation of contextual factors on entrepreneurial testing, but the role of funding status and the rigor of experiments remains underexamined. Theoretically, we add to past work by developing a model of how funding status could shape entrepreneurial rigor, by examining the moderating conditions such as novely and competition. Further, while this literature has a well developed theoretical base, we provide one of the first empirical investigations of the underlying theories in a high stakes setting. We also add to the literature on entrepreneurial finance that has examined the impact of startup funding on performance through many channels. We show how funders can shape startup outcomes through role in shaping experimentation and especially the rigor of early testing.

Our paper proceeds as follows: Section 2 describes the related literature and conceptual framework. Section 3 introduces the empirical setting and data. Section 4 presents the paper's main results, and Section 5 examines heterogeneity. Finally, Section 6 concludesx.

2 Literature and Conceptual Framework

2.1 Bayesian Entrepreneurship and Entrepreneurial Finance

Entrepreneurship involves decision-making under uncertainty (Gans, 2025). Rather than make large bets on ideas that may or may not work, generating data on the viability of the business or the technology through cheaper, early-stage tests dramatically changes the economics of entrepreneurship (Kerr et al., 2014). Entrepreneurs can invest in (cheaper) tests to prove the viability of their idea. Positive results can stimulate follow-on investment (and attract investors), while negative results

can mean that entrepreneurs abandon or pivot away from unpromising ideas before committing significant resources, thereby reducing wasted effort and capital. In fact, in industries like healthcare, early-stage testing is mandated by legislation and entrepreneurs must show efficacy and safety in early-stage clinical trials before proceeding with further development. In such contexts, validating risky ideas through early-stage testing is, therefore, particularly important.

While the importance of early-stage experimentation has been discussed and emphasized in entrepreneurship practice (Eisenmann et al., 2012; Blank et al., 2018), it is only recently that a research community has emerged around studying entrepreneurial experimentation using a scientific lens (Agrawal et al., 2025). In particular, this view emphasizes entrepreneurship as a bayesian process, with stakeholders possessing priors over the success of any given idea (with entrepreneurs being the most optimistic). Outcomes from staged investments (such as early-stage testing or customer interviews) provide signals on the viability of given ideas. Experimentation is therefore central to this view since it changes the posteriors of key stakeholders in the viability of a new business, which has important implications for their own actions and investments. More specifically, this research agenda rests on three premises (i) that key participants in entrepreneurial settings differ in their beliefs; (ii) that entrepreneurs tend to have more confident—or perhaps more optimistic—expectations about their ventures' chances of success compared to others; and (iii) that all parties update their beliefs using Bayes' rule as new information becomes available.

The central implication of this framework is that the choice of the experiment itself is endogenous to the priors of the stakeholders running them. In other words, since experiments differ both in terms of their cost and informativeness, stakeholders choose experiments that best align with their priors. Rigorous (and therefore more informative) experiments have a greater effect on updating posterior beliefs but are also more costly to run. Entrepreneurs are inherently optimistic about the chances of their business and prefer to run less rigorous experiments, and the potential for these experiments to affect their posterior beliefs is limited. This tendency may be especially pronounced in settings like healthcare, where early-stage experimentation is required. However, the specifics of trial design are increasingly flexible and left to the entrepreneur's discretion (U.S. Congress, 2016).

However, other stakeholders who might be more pessimistic about the chances of the business might choose different experiments. In particular, the Bayesian Entrepreneurship literature empha-

sizes the role of investors. Investors are likely to pick more rigorous experiments as compared to entrepreneurs since they need more robust information before making further commitments to an inherently risky project. While this overall framework, and the prediction that investors pick more rigorous experiments as compared to founders makes sense, rigorous empirical work that connects these theories to specific patterns is yet to emerge. In particular, even though multiple papers argue a connection between the key stakeholder (investor vs entrepreneur) and the design of experiments, we have very little empirical data linking the two (Agrawal et al., 2025). This is one goal of our study.

Further, our work also connects to a long-standing literature in entrepreneurial finance that examines the impact of investors on entrepreneurial success. This body of research has highlighted many channels through which investors shape the firms they invest in. These include providing guidance on hiring and building effective teams, leveraging their networks to help startups recruit key employees, and facilitating introductions to potential customers and strategic partners. Investors often offer general business advice, assist with refining business models, and help navigate regulatory and operational challenges. They may also play a role in setting milestones, monitoring progress, and providing credibility that can attract additional resources or partnerships. In some cases, investors help startups access follow-on financing, improve governance structures, and professionalize management practices (Gompers and Lerner, 2001; Hellmann and Puri, 2002). Further, this literature has looked at the role of experimentation in driving financing decisions and outcomes (Kerr et al., 2014). Yet this work has not yet looked at how investment (and therefore investors) affects the choice of which experiments a startup might run. This is a key gap that we consider in this paper. One interesting paper that connects the two approaches is Nanda (2024), which connects the entrepreneurial finance literature to the recent work on bayesian entrepreneurship. This conceptual paper makes predicts that "Investors value more rigorous experiments ... because it reduces the likelihood of them having to commit further funding to a venture due to a 'false positive'." It is this prediction that we test in this paper.

2.2 Factors Influencing the Effect of Venture Financing on Experimentation Rigor

While the general prediction that startup financing will lead to more rigorous experiments has recently seen some theoretical support, it is not clear whether this effect will necessarily be uniform across different settings. It is possible that the gap between the investor's and entrepreneur's priors is itself shaped by external factors that then influence the investors' desire to run more rigorous experiments post-investment. In particular, we focus on three key conditions.

First, novel technologies differ from established ones in that their technical feasibility is much less certain, because there is limited prior evidence or track record to indicate whether they will work as intended (Krieger et al., 2022). This heightened uncertainty makes them especially risky, as there is little prior evidence to guide expectations. As a result, the gap between entrepreneur and investor priors may be particularly high, with entrepreneurs tending to be more optimistic and investors more cautious (Nanda and Rhodes-Kropf, 2017). Therefore, for novel technologies, investors might be particularly adamant about seeking more rigorous testing in the early-stages of the venture.

Second, investor priors will also be a function of the competitive nature of the technology. A large literature in innovation economics and management has pointed to the important role of competition in shaping new entrepreneurial activity (for an overview, see Cohen, 2010). In particular, when a number of other firms are involved in commercializing technology in a given area, there are fewer question marks about the product's scientific and commercial viability, which in turn reduces the gap in expectations between investors and entrepreneurs. Further, even if competitors are using different technologies, the general sense that any alternate technology might be viable, provides confidence that a given market opportunity is "solveable," which also increases investor confidence. Further, going beyond the idea of bayesian priors, racing dynamics might take over in competitive markets (Hill and Stein, 2025) and it might become important to establish a positive result to get to market quickly rather than spend longer on rigorous and more expensive early-stage experimentation. Therefore, in markets with a lower level of competition, we should expect that investors demand less rigorous experiments and in markets with less competition, their

need to run more rigorous experiments is particularly high.

Finally, an investor's priors are shaped by their past industry experience. In any industry, we tend to see specialized investors who invest only in their domain, and others who are generalists, investing across domains. For example, in healthcare, there are two main types of investors: specialized healthcare investors, who focus primarily on the healthcare sector and possess deep domain expertise, and more generalist investors, who invest across a range of industries but may also allocate capital to healthcare ventures. When considering this variation, we expect domain experts will have lower priors about the likelihood of success, since they are acutely aware of the many challenges and potential points of failure unique to that field. Past work has shown that insiders tend to be harsher about the prospects of new ideas as compared to outsiders (Li, 2017). As a result, these specialized investors are likely to demand more rigorous experiments and higher standards of evidence after providing funding, compared to generalist investors who may not fully appreciate all the ways a venture can fail. For example, in healthcare, specialized healthcare investors possess deep domain expertise and are more attuned to the scientific, regulatory, and operational hurdles, leading them to require more robust early-stage testing than generalist investors who invest across a range of industries.

Altogether, in addition to the prediction that ventures are likely to run more rigorous experiments post VC investment, we expect this increase to be particularly large under conditions of high novelty, low competition, and for domain-specific investors. These hypotheses enrich past work in Bayesian entrepreneurship and entrepreneurial finance by applying these frameworks to understand not only whether investors increase experimental rigor, but also how this effect is moderated by the context in which ventures operate and the characteristics of the investors themselves.

2.3 A Simple Model of VC Financing and Experimentation

To fix ideas, this section provides a simple theoretical framework that clarifies how VC financing may shape firms' experimentation decisions. In particular, we show the quality (i.e., informativeness, rigor) of startup's experiment depends on beliefs about project success, and how this may differ between startups and VCs. The model also highlights how experimentation choices may vary with

project novelty, competition, and investor specialization. We then test these empirically assess these empirically in the sections that follow.

2.3.1 Set-up

Consider a startup i that initiates a project that yields payoff $V > 0$ if successful, and 0 otherwise. The startup believes that the project will succeed with probability μ_i and the cost of commercialization is C. As a result, the expected value of commercialization is $\mu_i(V - C)$.

Before deciding whether to commercialize the project, the startup may conduct an experiment that generates a signal $s \in \{0, 1\}$, where $s = 1$ is interpreted as a favorable outcome. The startup commercializes the project only if $s = 1$. The quality of the experiment is shaped by $\lambda \in (0.5, 1)$, where $\lambda = \Pr(s = 1 \mid \text{Success}) = \Pr(s = 0 \mid \text{Failure})$. In other words, the signal is symmetric and informative, and higher levels of λ reflect higher-quality experiments. Suppose that $c(\lambda)$ where $c(\lambda) > 0$ and $c'(\lambda) > 0$, such that higher quality experiments are more expensive.

The startup's expected payoff from running an experiment with quality λ is: $\Pi_i = \lambda\mu_i(V - C) - (1 - \lambda)(1 - \mu_i)C - c(\lambda)$. The first term $\lambda\mu_i(V - C)$ reflects the payoff from true positives (commercializing good projects following a favorable signal), $(1 - \lambda)(1 - \mu_i)C$ reflects the cost of false positives (commercializing bad projects following a favorable signal), and $c(\lambda)$ reflects the cost of experimentation.

The startup's optimal choice of experiment quality, λ^*, satisfies:

$$\mu_i V - (2\mu_i - 1)C = c'(\lambda^*) \tag{1}$$

2.3.2 Effect of VC Financing on Trial Design

In this section, we consider how VC financing shapes experimental design. Relative to startups, VCs are more pessimistic (i.e., hold lower priors) about the success of a potential project, such that $\mu_v < \mu_i$. As a result, the effect of VC financing on experimentation corresponds to considering how the optimal λ^* responds to changes in μ.

From Equation (1) above, the relationship between priors (μ) and experiment quality (λ) depends on the relative sizes of V and C. When $V < 2C$ (i.e., false positives are costly), then a

decrease in μ is associated with an increase in $\lambda*$, In words, being more pessimistic increases the value of high-quality signals, which can then help avoid costly mistakes.

This leads to the main prediction of the paper: Following VC investment, startups conduct more rigorous experiments.

2.3.3 Heterogeneity

This simple model also generates predictions for how the effect of VC financing on experimentation varies across novelty, competition, and funders.

First, more novel projects are associated with greater scientific and commercialization uncertainty, which lowers a VC's belief in the likelihood of success (i.e., reduces μ_v). According to Equation (1), this leads to a higher λ^*. A key prediction is therefore: Following VC funding, the increase in trial quality is greater for more novel projects.

Second, in markets with more prior startup activity, VCs may learn from the outcomes of prior startups. This access to information effectively increases VCs' optimism in the viability of a project (i.e., increases μ_v), reducing the need for high λ^*. As a result, we expect that following VC funding, the increase in trial quality is lower among projects with greater levels of prior competition.

Finally, specialized VCs may be more aware of scientific and commercialization challenges, leading to more conservative expectations about the success of a project (i.e., lower μ_v). As a result, they may place more value on high-quality experimentation. A key prediction is therefore: The increase in trial quality following VC funding is greater the VC is specialized.

3 Setting and Data

3.1 Biopharmaceutical Experimentation

The U.S. biopharmaceutical industry provides a useful setting to examine how shifts in firms change experimentation decisions in response to funding. In the biopharmaceutical context, experimentation takes the form of a series of clinical trials, in which costs increase with each subsequent phase. These trials progress from phase I, which tests safety in a small patient group; to phase II, which tests safety and efficacy in a larger patient group; to phase III, which assesses safety and efficacy

in a larger population over a longer period. If their phase III clinical trials are successful, drug manufacturers seeking regulatory approval of a novel drug to treat a specific disease must submit a New Drug Application containing clinical trial data to the FDA.

Against this backdrop, a key decision for biopharmaceutical startups is how to design their clinical trials.[1] For startups, investing in rigorous trial design involves making a trade-off between generating high-quality evidence (i.e., evidence less subject to biases) and managing the additional costs, time, and complexity associated with more rigorous design decisions. For instance, randomized-controlled trials are considered the "gold standard" for establishing the causal impact of drugs on safety and efficacy (U.S. Food and Drug Administration, 2022). They are widely viewed as the highest form of evidence on which to base approval and treatment decisions (Ioannidis, 2005). By randomly assigning patients to treatments and control groups, randomized controlled trials aim to minimize potential biases that can be introduced through patient selection. These design decisions are particularly salient in late-stage trials (e.g., Phases II and III) where the evidence generated on safety and efficacy on larger patient populations is most important for regulatory approval and treatment decisions.

3.2 Biopharmaceutical Startups and VC Financing

The drug development process is long, costly, and risky. Estimates suggest that less than 12% of drugs that begin clinical trials successfully advance to market (DiMasi et al., 2016). The average cost of developing a new drug exceeds $2.6 billion, and development timelines often span over a decade. These high costs and risks are especially salient for biopharmaceutical startups, which typically lack the capital and expertise needed to navigate the drug development and regulatory approval process.

To address these constraints, startups often turn to VCs for funding and guidance (Agrawal et al., 2025). In addition to providing financial support, VCs can play an active role in shaping the direction of biopharmaceutical startups' R&D decisions. They can help offer access to scientific, managerial, and regulatory expertise; define development strategies; and set key milestones. As of the first quarter of 2025, healthcare is the second-largest sector for VC investment, following

[1] https://methods.cochrane.org/bias/assessing-risk-bias-included-studies

information technology (Grabow, 2025).

3.3 Dataset Construction

To examine the relationship between VC funding and clinical trial design among startups, we focus on activity among early-stage biopharmaceutical startups. Using data from Pitchbook, we identify all startups with U.S. headquarters classified in the "Pharmaceuticals & Biotechnology" industry that have received pre-venture and venture funding. For each startup, we collect information on the startup's name, founding year, headquarters location, and funding history.

We focus on startup funding from VC deals. We identify VC deals as those classified as "Early Stage VC," "Later Stage VC," and "Seed Round." For each VC funding event, we identify the date, deal type, investor name, and (when available) the funding amount. We use the earliest VC deal date as a proxy for the timing of the startup's initial VC financing.

To characterize each startup's research activity, we incorporate clinical trial data from Clarivate Analytics' Cortellis Competitive Intelligence and Clarivate Analytics' Cortellis Clinical Trials Intelligence (hereafter, "Cortellis"). We focus on the subset of startups that are research-active (i.e., have ever had clinical trials). We focus on investment in Phase II and Phase III clinical trials as, unlike early-stage trials, they are publicly reported, involve more standardized trial design, and constitute a significant R&D investment. Since clinical trial reporting improves over time, we restrict the sample period from 1998 (or the startup's founding year, whichever is later) to 2022. Our final dataset consists of 26,179 startup-year observations and 1,843 unique startups.

Next, we collect data on measures of trial design quality, product novelty, competition, and funder specialization.

Trial Design Quality. We construct measures of trial design quality. Determining the actual quality of clinical trial design is inherently challenging as it can depend on a variety of complex, unobservable, difficult-to-measure factors, such as the study population, the validity of trial endpoints, and the appropriateness of the statistical design. In the absence of these measures, we focus on three commonly used indicators of rigorous trial design (U.S. Food and Drug Administration, 2006): whether the trial includes randomization (e.g., patients are randomly assigned to treatment

versus control arms), blinding (e.g., neither participants nor investigators know which treatment is administered), and a comparator group (e.g., a placebo or active control to benchmark the treatment effect).

Product Novelty. To proxy for product novelty, we focus on the technological novelty of the tested drug's mechanism of action. A drug's mechanism of action is the biochemical mechanism through which it achieves its effects. For example, poly[ADP-ribose] polymerase (PARP) inhibitors produce an anticancer effect by preventing damaged cancerous cells from repairing themselves. A trial is classified as "novel" if it involves drugs whose mechanism of action was first introduced in clinical trials within the past two years. All other trials are classified as "non-novel."

Competition. To proxy for the level of competition a startup faces in a given year, we focus on the level of competitive activity within the disease areas in which the startup conducts trials. This is motivated by the idea that startups operating in more crowded disease areas face more competitive pressure. Specifically, for each startup-year, we identify all clinical trials conducted by the startups and the diseases (as measured by ICD-9 codes) they are conducted in. For each trial, we count the number of competitor Phase III trials in the same diseases in the same year. We then measure the startup's average competition by summing the total number of competitor trials across all trials and dividing by the number of trials conducted by the startup. To measure recent competition, we sum this weighted average over the previous five years. For example, suppose a startup conducted two trials over the past five years: one in a disease with one competitor Phase III trial and another in a disease with four competitor Phase III trials. Its weighted competition measure would be $\frac{1+4}{1+1} = 2.5$ competitor trials. With this weighted competition measure, we classify a startup-year as facing "high competition" if its five-year weighted measure is above the sample median for that year; all other startup-years are classified as facing "low competition."

Funder Specialization. We aim to distinguish between investors with specialized expertise in the pharmaceutical industry and those that are domain agnostic. As described in Section 2, this is motivated by the idea that investors who are specialized healthcare are more likely to understand the scientific, regulatory, and commercialization challenges unique to drug development. To capture these differences, we use data from Pitchbook to classify VCs into two categories. We define

an investor as a "Health Investor" if their preferred industries include healthcare categories (e.g., "Pharmaceuticals," "Drug Discovery," and "Clinical Trials"); others are classified as "Non-Health Investors."

Table 1 presents summary statistics on our startup-year level dataset. Among the 26,179 startup-year observations, approximately 66% experience VC funding with an average funding year of 2012. Although detailed reporting on VC funding amounts is limited, in our sample, the average reporting initial VC funding amount is $12 million, with a median of $4.7 million. Online Appendix Figure A1 shows the timing of investment by plotting the cumulative distribution of VC funding across startups over time.

Clinical trials are rare: only 11% of startup-years have any Phase II or Phase III trials. Among startups conducting trials, the majority include high-quality design features, such as randomization, blinding, and using a comparator group. Figure 1 shows the substantial variation in trial design quality across firm-years. Additional characteristics indicate that trials are more commonly associated with novel (vs. non-novel) technologies, startups face relatively low (vs. high) competition, and startups are more likely to receive funding from health (vs. non-health) investors.

4 Main Results

4.1 Empirical Strategy

Using this data, we examine the relationship between VC funding and biopharmaceutical startups' clinical trial decisions. For each startup-year observation it, we estimate the following:

$$Y_{it} = \beta PostFunded_{it} + \delta_i + \delta_t + \epsilon_{it} \tag{2}$$

where Y_{it} is an indicator for clinical trial type (e.g., any trial, any randomized trial) and $PostFunded_{it}$ is an indicator for whether startup i has received VC funding by year t. Our main regressions include startup fixed effects (δ_i) and year fixed effects (δ_t). Robust standard errors are clustered at the startup level. Unless otherwise noted, coefficients are derived from OLS regressions.

Our coefficient of interest is β which represents the causal effect of VC funding on clinical trial activity by startup i in a given year t.

4.2 Baseline Results

Column 1 of Table 2 shows that across all startups, VC funding increases clinical trial activity. In particular, VC funding is associated with a yearly 0.10 percentage point ($96\% \approx \frac{0.108}{0.113} \times 100$) relative increase in the probability that a startup conducts a clinical trial.

Columns 2 to 7 of Table 2 highlight that this increase is driven by substantial heterogeneity in trial design quality. Using seemingly unrelated regressions, which permit a direct comparison of coefficients, we find that VC funding disproportionately increases the probability of trials with high-quality designs. For example, a comparison of columns 2 and 3 shows that the likelihood of a randomized trial increases by 0.08 percentage points, while non-randomized trials increase by 0.02. We see similar trends among blinded trials and trials with comparator groups, suggesting that VC funding is associated with overall increases in trial quality.

To explore the timing of the estimated impact on clinical trials, we estimate an event study version of Equation (2) where the single indicator variable $PostFunded_{it}$ is replaced with a vector of indicator variables for each year before and after the startup's initial VC investment. Providing support for our identification strategy, Panel A of Figure 2 shows that the probability of any clinical trial does not change differentially across startups before their initial VC funding. However, the probability of a clinical trial increases differentially for startups that receive VC funding and remains higher afterward. Startups shift their clinical trial decisions relatively quickly: on average, startups increase their clinical trials in the first year they receive funding.

Panels B to D of Figure 2 reveal similar patterns when examining differences by trial design quality. Panel B shows a significant and persistent increase in the likelihood of a randomized trial, which is disproportionately larger than the increase in the likelihood of a non-randomized trial. While trials with and without blinding (Panel C) or comparator groups (Panel D) both increase after VC investment, the relative differences are less salient, though the effects still consistently favor high-quality designs.

4.3 Robustness and Alternative Explanations

Before examining heterogeneity by product novelty, competition, and funder specialization, we probe the robustness of results and consider alternative explanations.

4.3.1 Alternative Specifications

Our baseline results focus on the extensive margin effects of VC funding on clinical trial activity. Online Appendix Table A2 shows that VC funding has similar effects along the intensive margin: VC funding is associated with a 6 percent ($\approx (e^{0.0586} - 1) \times 100$) increase in the number of randomized trials, a statistically significantly higher increase than the 2 percent ($\approx (e^{0.0174} - 1) \times 100$) increase in non-randomized trials. We observe qualitatively similar patterns for trials by blinding and comparator use, though the differences between blinded and non-blinded trials are not statistically significant.

4.3.2 Staggered Treatment

A recent literature in econometrics has demonstrated that staggered difference-in-differences models can lead to average DID estimates that are biased (Roth et al., 2023). In Online Appendix Figure A4, we show that our results are robust to using the alternative estimator proposed by Callaway and Sant'Anna (2021).

4.3.3 Easing Capital Constraints

In considering the impact of VC funding on startups' clinical trial design quality decisions, one potential alternative explanation for the disproportionate increase in high-quality trials following VC funding is that those trials are more costly to conduct. For example, randomization of patients across treatment and control arms requires more patients and additional expertise to manage the design complexity. VC funding may ease capital constraints that startups can then use to invest in more high-quality trial designs. If (easing) financial constraints were a key driver, we expect the effect of VC funding on trial quality to be larger for startups facing greater pre-VC funding constraints.

While we cannot directly measure a startup's capital constraints, we use startup age as a proxy: younger startups are more likely to have less access to capital for R&D and be financially constrained (Hadlock and Pierce, 2010). We classify startups as "old" if their age at the time of funding is above the median (2 years) among all funded startups; all other startups are considered "young."

Online Appendix Table A6 shows that the effect of VC funding on startups' trial design decisions does not vary significantly between young and old startups. Although this does not rule out a potential role of capital constraints, it does suggest that they are unlikely to be a primary driver behind the disproportionate increase in high-quality trials.

4.3.4 Regulatory Expectations

Another potential concern is that regulatory expectations may drive the observed relationship between VC funding and trial design. For example, if regulatory requirements for clinical trials have increased over time, this could bias our estimates. Note, however, trial design requirements have generally become more flexible over time, which would likely bias us against finding a positive relationship between VC funding and trial quality. Another possibility is that regulatory expectations vary by disease area (U.S. Food and Drug Administration, 2014), and that VC funding causes startups to shift towards diseases with more stringent requirements. To empirically address these concerns, we conduct two additional analyses.

First, we examine whether the relationship between VC funding and trial quality changes over time. Specifically, we compare estimates before and after the enactment of the 21st Century Cures Act in 2016 (U.S. Congress, 2016). The 21st Century Cures Act was designed to expedite the drug development and approval process and encouraged the use of adaptive trial designs. Adaptive trial designs are a flexible approach to trial design that allows for certain aspects of the trial to be changed (e.g., new treatment arms, changes in randomization) based on data collected during the trial. Online Appendix Table A4 shows that the relationship between VC funding and trial design remains largely the same before and after the policy.

Second, we account for potential disease-level differences in regulatory expectations by estimating a startup-disease-year version of Equation (2) which includes disease fixed effects. We define diseases using both narrow ICD-9 codes (e.g., "Malignant neoplasm of brain" and "Malignant neo-

plasm of eye") and broader ICD-9 chapters (e.g., "Neoplasms"). Online Appendix Table A5 shows that the relationship between VC funding and trial design holds across both disease measures.

Taken together, these results support the view that regulatory expectations are unlikely to drive our main results.

5 Heterogeneity by Novelty, Competition, and Funder

5.1 Novelty

While the baseline results show that VC investment leads to a disproportionate increase in high-quality trials, these averages may mask important heterogeneity. As discussed in Section 2, the impact of VC funding on trial design may depend on the novelty of the product under development. VCs funding startups with more novel products may perceive greater risk in their investments and as a result, require more rigorous clinical trials to reduce concerns about the scientific and commercial viability of their investment.

To investigate this possibility, we incorporate information about product novelty (as described in Section 3.3). We adapt the DiD specification in Equation (2) to separately examine the impact of VC funding on trial design quality for novel and non-novel trials. Figure 3 graphically presents the results for the three quality dimensions. The corresponding estimates can be found in Online Appendix Table A3.

The first set of bars in Panel A shows that for trials testing novel technologies, VC funding leads to a disproportionately greater increase in randomized trials relative to non-randomized trials. In contrast, the next set of bars in Panel A shows that, for trials testing non-novel technologies, the difference between randomized and non-randomized trials is not statistically significant. Panels B and C show similar patterns for the use of blinding and comparators, though the estimates are less precise. These heterogeneous effects, which were masked in the baseline results, imply that VC funding is more likely to lead to increases in high-quality trials when startups are testing novel technologies.

5.2 Competition

To complement our previous analyses, we examine how product market competition shapes startups' trial design decisions. Higher levels of prior competitor activity within a disease may provide investors with more information regarding the scientific and commercial viability of investments in that disease. This may reduce the need for any given startup to generate high-quality evidence themselves.[2]

Thus, we examine whether startups' trial design responses to VC funding are shaped by the level of competition they face. Table 3 shows that across all three dimensions of trial quality (randomization, blinding, comparator use) startups facing high levels of competition are significantly less likely to increase investment in high-quality trials after they receive VC funding; in contrast, startups in less competitive markets show a significant shift towards high-quality trials. For example, column 1 shows that receiving VC funding increases the likelihood of a randomized trial by 0.06 percentage points among startups facing low levels of competition, while it decreases by 0.05 percentage points among startups facing high levels of competition. These findings are consistent with the view that in crowded markets, investors may rely on other signals of product quality, lowering the need for additional high-quality trials.

5.3 Funder Specialization

The previous analyses suggest that startups are more likely to invest in high-quality trials in settings with high uncertainty (e.g., when products are novel or when product markets have limited prior research activity). As discussed in Section 2, the ability to recognize such uncertainty may vary by funder specialization. In particular, VCs with more specialized expertise in the pharmaceutical industry may be more aware of scientific, regulatory, and commercialization challenges, and therefore, may require high-quality evidence to lower the risk of their investments.

To examine the role of funder specialization, we compare how startups shift their trial design choices in response to initial funding from health vs. non-health VCs. Table 4 reveals two im-

[2] An additional explanation is that startups facing high levels of competition may be incentivized "cut corners" in trial design in order to obtain first mover advantages (Hill and Stein, 2025).

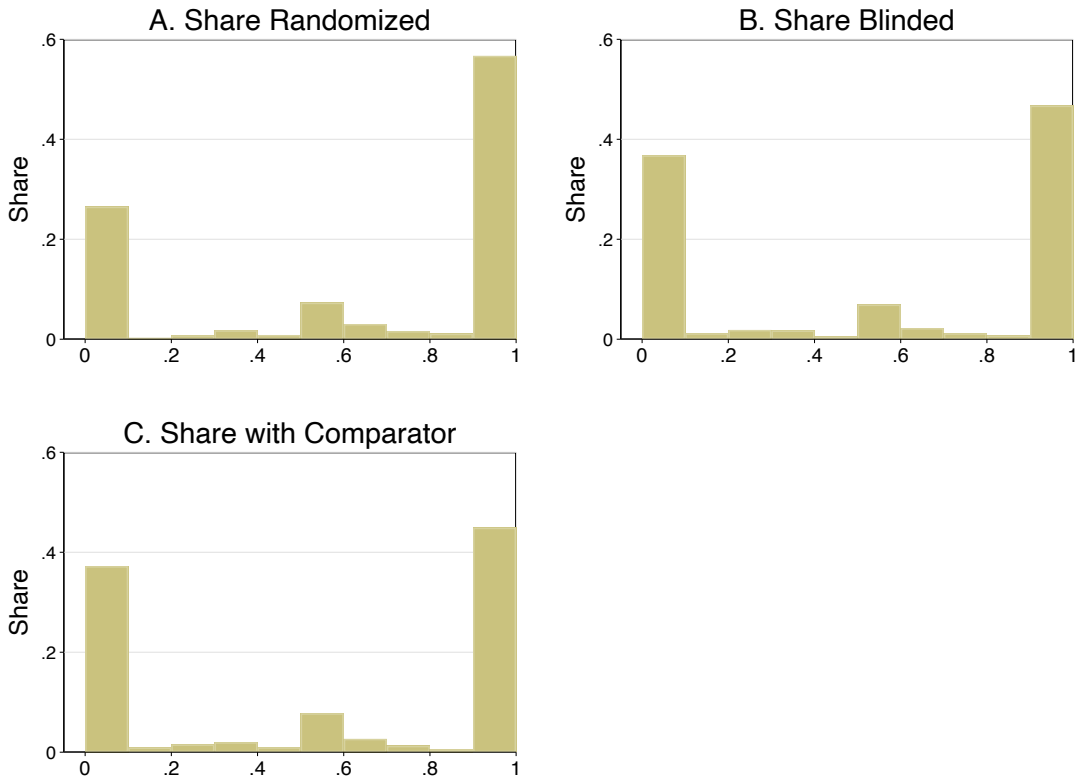
portant facts. First, when startups receive funding from health investors, they are significantly more likely to conduct high-quality trials compared to when they receive funding from non-health investors. Second, following investment from health investors, the increase in high-quality trials is disproportionately greater than in low-quality trials. Taken together, these results suggest that funder specialization plays an important role in shaping startups' trial design quality.

6 Conclusion

In this paper, we investigate how VC financing shapes startups' experimentation decisions. Our conceptual framework clarifies how external stakeholders with more pessimistic priors can shape the rigor of startups' experiments. We then examine this dynamic in the context of the healthcare industry, where biopharmaceutical startups must conduct clinical trials to generate data on product safety and efficacy. Using detailed data on clinical trials and VC funding events, we find that VC funding increases the likelihood that startups conduct more rigorous trials. This increase is larger for trials testing novel products and those funded by specialized investors, but moderated in more competitive environments. Together, these findings highlight the endogenous nature of experimental design and the role of financing in shaping the investments towards more rigorous data generation.

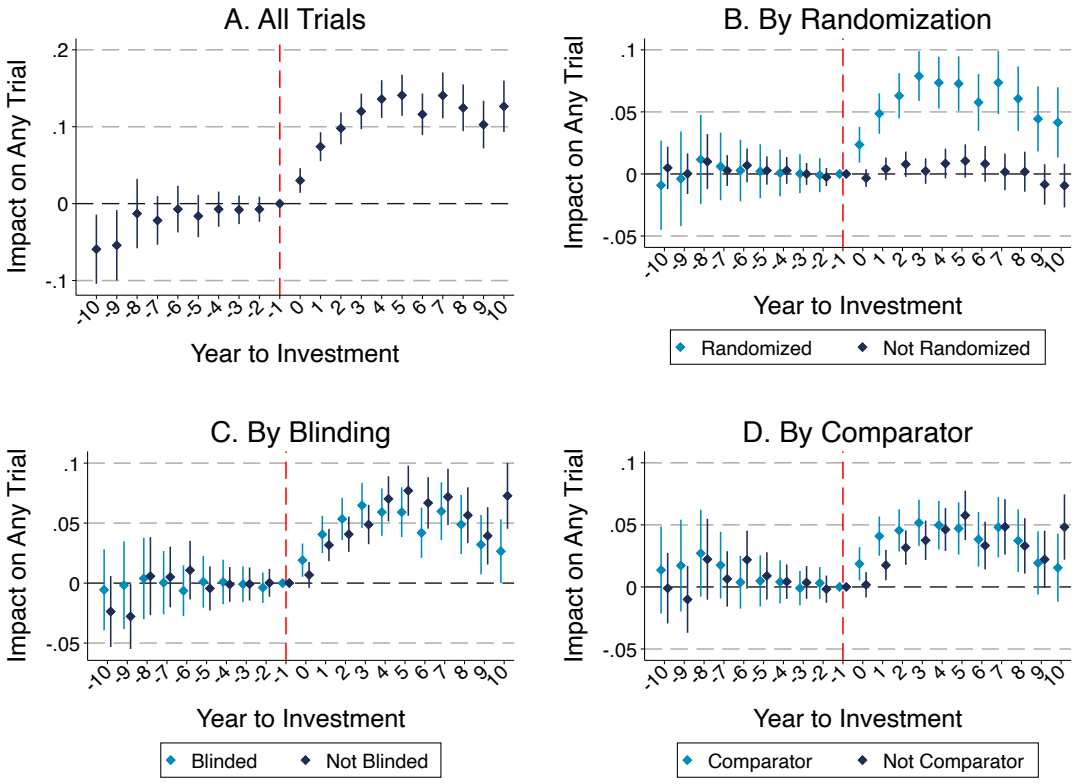
Figures and Tables

Figure 1: Variation in Trial Design Quality



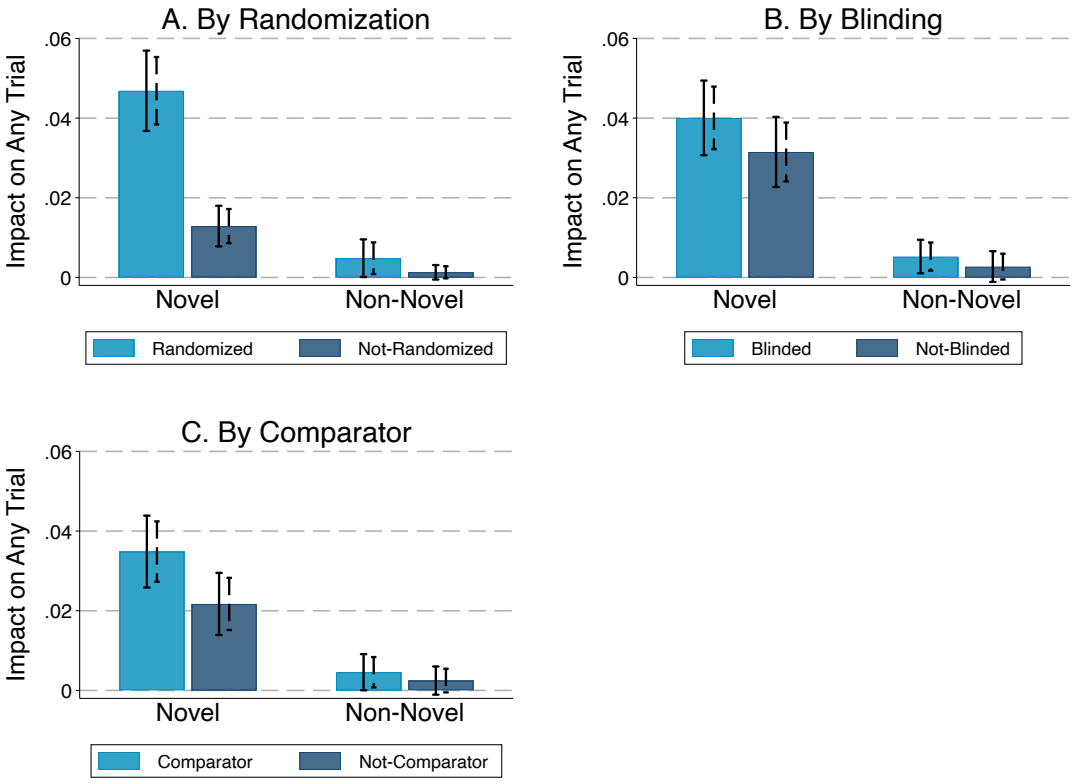
Note: This figure presents the variation in trial design quality across firm-years. Panel A presents the share of trials that are randomized, Panel B presents the share of trials that are blinded, and Panel C presents the share of trials that have a comparator.

Figure 2: Effect of VC Funding on Trial Design Quality



Note: This figure presents event study coefficients from the estimation of equation (2) on overall trial investment on for trials of different design quality. Shown are coefficients in the 10 years leading and following the initial funding event. Coefficients are estimated from startup-year level OLS regressions with startup fixed effects and year fixed effects. The outcome is an indicator for any trial (Panel A), any trial that is randomized or not randomized (Panel B), any trial that is blinded or not blinded (Panel C), or any trial that has a comparator or no comparator (Panel D). Solid vertical lines represent 95% confidence intervals. The dotted vertical line represents the year before the initial funding.

Figure 3: Effect of VC Funding on Trial Design Quality, by Novelty



Note: This figure examines how the effect of VC funding on trial design varies by the novelty of the tested technology. A trial is classified as "novel" if it tests drugs whose mechanism of action was first introduced in clinical trials within the past two years. All other trials are classified as "non-novel." Shown are coefficients from startup-year level OLS regressions with startup fixed effects and year fixed effects. Outcomes are binary indicators for certain types of clinical trials. For example, the first bar in Panel A represents the effect of VC funding on the likelihood of any randomized and novel clinical trial. The solid vertical lines represents 95% confidence intervals and the dotted vertical lines represents 90% confidence intervals.

Table 1: Summary Statistics: Startup-Year Level

	Mean (1)	SD (2)	Min (3)	Max (4)
A. VC Funding				
Any VC Funding	0.66	0.47	0	1
VC Funding Year	2011.60	6.21	1998	2021
B. Trial Levels and Quality				
Any Trial	0.11	0.32	0	1
Any Randomized Trials	0.08	0.28	0	1
Any Not Randomized Trial	0.02	0.14	0	1
Any Blinded Trial	0.07	0.26	0	1
Any Not Blinded Trial	0.06	0.24	0	1
Any Comparator Trial	0.07	0.26	0	1
Any No Comparator Trial	0.05	0.22	0	1
C. Technology Novelty, Competition, and Investor Type				
Any Trial With Novel Technology	0.08	0.27	0	1
Any Trial With Non-Novel Technology	0.02	0.12	0	1
Firm With High Competition	0.07	0.25	0	1
Firm With Low Competition	0.93	0.25	0	1
Any VC Funding from Health Investor	0.58	0.49	0	1
Any VC Funding from Non-Health Investor	0.04	0.20	0	1

Note: This table presents summary statistics at the startup-year level. The startup-year sample consists of 26,179 startup-years and 1,843 unique startups.

Table 2: Effect of VC Funding on Trial Design Quality

	Dependent Variable: Any Trial						
	All	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Funded	0.108***	0.0770***	0.0174***	0.0673***	0.0437***	0.0608***	0.0319***
	(0.00739)	(0.00627)	(0.00297)	(0.00593)	(0.00520)	(0.00587)	(0.00464)
Mean of Dep. Var.	0.113	0.083	0.021	0.072	0.059	0.071	0.052
Diff. Wald Test p-value		0.00		0.00		0.00	
Observations	26,179	26,179	26,179	26,179	26,179	26,179	26,179
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality. The level of observation is at the startup-year. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. Column 1 is estimated using OLS. The "Wald Test p-value" is the p-value comparing the $Post \times Funded$ coefficient in columns 2 vs. 3, columns 4 vs. 5, columns 6 vs. 7. Columns 2 to 7 are estimated using seemingly unrelated regressions. Standard errors are clustered at the startup level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of VC Funding on Trial Design Quality, by Competition

	Dependent Variable: Any Trial					
	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Funded × High Comp	-0.111***	-0.0523*	-0.0924**	-0.0597	-0.0948**	-0.0354
	(0.0364)	(0.0315)	(0.0422)	(0.0401)	(0.0397)	(0.0400)
Post × Funded	0.0560***	0.0121***	0.0496***	0.0254***	0.0427***	0.0158***
	(0.00509)	(0.00273)	(0.00502)	(0.00411)	(0.00488)	(0.00381)
High Comp	0.554***	0.172***	0.467***	0.434***	0.477***	0.361***
	(0.0315)	(0.0291)	(0.0374)	(0.0361)	(0.0351)	(0.0365)
Mean of Dep. Var.	0.0830	0.0213	0.0716	0.0593	0.0710	0.0520
Observations	26,179	26,179	26,179	26,179	26,179	26,179
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality, by competition. The level of observation is at the startup-year. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. For a given startup-year observation, $HighComp$ is equal to one if the weighted number of phase III trials over the prior five years in the same ICD9 code the startup has conducted clinical trials in is above the median. Controls include startup fixed effects and year fixed effects. Estimates are from OLS regressions. Standard errors are clustered at the startup level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Effect of VC Funding on Trial Design Quality, by Funder Specialization

	Dependent Variable: Any Trial					
	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Funded × HealthInvestor	0.0740***	0.0184***	0.0649***	0.0480***	0.0595***	0.0358***
	(0.00658)	(0.00317)	(0.00631)	(0.00559)	(0.00634)	(0.00504)
Post × Funded × NonHealthInvestor	0.0323**	0.00604	0.0205	0.0110	0.0311*	-0.00339
	(0.0160)	(0.00722)	(0.0159)	(0.0133)	(0.0161)	(0.0125)
Mean of Dep. Var.	0.0830	0.0213	0.0716	0.0593	0.0710	0.0520
Observations	26,179	26,179	26,179	26,179	26,179	26,179
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality, by funder specialization. The level of observation is at the startup-year. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. All regressions are estimated using OLS regressions. Standard errors are clustered at the startup level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

References

Agrawal, A., Camuffo, A., Gambardella, A., Gans, J. S., Scott, E. L., and Stern, S. (2025). *Bayesian Entrepreneurship*. MIT Press. Forthcoming, based on document date February 22, 2025.

Blank, S. et al. (2018). Why the lean start-up changes everything.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences With Multiple Time Periods. *Journal of Econometrics*, 225(2):200–230.

Camuffo, A., Gambardella, A., Messinese, D., Novelli, E., Paolucci, E., and Spina, C. (2024). A scientific approach to entrepreneurial decision-making: Large-scale replication and extension. *Strategic Management Journal*, 45(6):1209–1237.

Cohen, W. (2010). Chapter 4–Fifty Years of Empirical Studies of Innovative Activity and Performance. Handbook of the Economics of Innovation. HH Bronwyn and R. Nathan.

DiMasi, J. A., Grabowski, H. G., and Hansen, R. W. (2016). Innovation in the pharmaceutical industry: new estimates of R&D costs. *Journal of health economics*, 47:20–33.

Eisenmann, T. R., Ries, E., and Dillard, S. (2012). Hypothesis-driven entrepreneurship: The lean startup. *Harvard business school entrepreneurial management case*, (812-095).

Gans, J. S. (2025). Knightian Uncertainty and Bayesian Entrepreneurship. Technical report, National Bureau of Economic Research.

Gompers, P. and Lerner, J. (2001). The venture capital revolution. *Journal of economic perspectives*, 15(2):145–168.

Grabow, J. (2025). Massive AI deal supercharges VC results in Q1 2025. EY US Insights. "Information technology represented 74

Hadlock, C. J. and Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The review of financial studies*, 23(5):1909–1940.

Hellmann, T. and Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The journal of finance*, 57(1):169–197.

Hill, R. and Stein, C. (2025). Race to the bottom: Competition and quality in science. *The Quarterly Journal of Economics*, page qjaf010.

Ioannidis, J. P. (2005). Why most published research findings are false. *PLoS medicine*, 2(8):e124.

Kaplan, R. M., Koong, A. J., and Irvin, V. (2023). Review of evidence supporting 2022 US Food and Drug Administration drug approvals. *JAMA Network Open*, 6(8):e2327650–e2327650.

Kerr, W. R., Nanda, R., and Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives*, 28(3):25–48.

Krieger, J., Li, D., and Papanikolaou, D. (2022). Missing novelty in drug development. *The Review of Financial Studies*, 35(2):636–679.

Li, D. (2017). Expertise versus Bias in Evaluation: Evidence from the NIH. *American Economic Journal: Applied Economics*, 9(2):60–92.

Nanda, R. (2024). Priors, Experiments, Learning and Persuasion in (Bayesian) Entrepreneurial Finance.

Nanda, R. and Rhodes-Kropf, M. (2017). Financing risk and innovation. *Management science*, 63(4):901–918.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's Trending in Difference-in-differences? A Synthesis of the Recent Econometrics Literature. *Journal of Econometrics*.

U.S. Congress (1997). Food and Drug Administration Modernization Act of 1997. https://www.govinfo.gov/content/pkg/PLAW-105publ115/pdf/PLAW-105publ115.pdf. Public Law 105-115.

U.S. Congress (2007). Food and Drug Administration Amendments Act of 2007. https://www.congress.gov/110/plaws/publ85/PLAW-110publ85.pdf. Public Law 110-85.

U.S. Congress (2016). 21st Century Cures Act. https://www.congress.gov/114/plaws/publ255/PLAW-114publ255.pdf. 130 Stat. 1033.

U.S. Food and Drug Administration (2006). The Drug Development Process: Phases of Clinical Trials. https://www.fda.gov/media/71349/download. Accessed: 2025-06-03.

U.S. Food and Drug Administration (2014). Expedited Programs for Serious Conditions – Drugs and Biologics. https://www.fda.gov/files/drugs/published/Expedited-Programs-for-Serious-Conditions-Drugs-and-Biologics.pdf. Guidance for Industry; contains non-binding recommendations on fast track, breakthrough therapy, accelerated approval, and priority review designations.

U.S. Food and Drug Administration (2022). Designing Sound Clinical Trials That Incorporate Real-World Data. https://www.fda.gov/drugs/regulatory-science-action/designing-sound-clinical-trials-incorporate-real-world-data. Accessed: 2025-06-02.

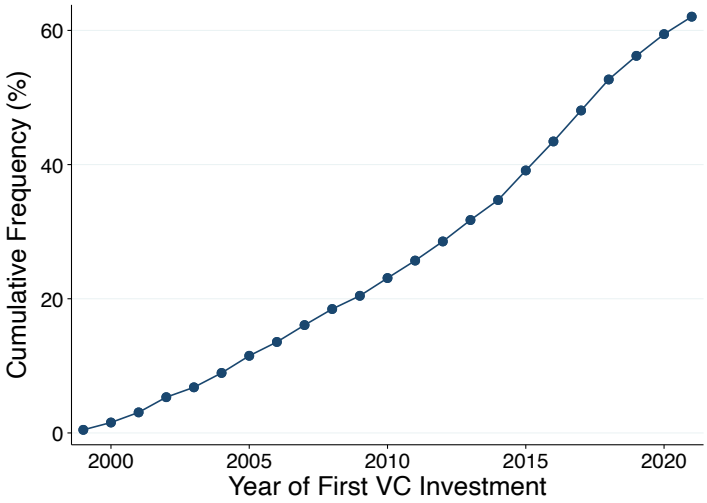
Appendix Figures and Tables

Table A1: Summary Statistics: Startup-Year Level, By VC Investment

	No VC Funding (N = 8,839 firm-year)		VC Funding (N = 17,340 firm-year)		T-test *p*-value
	Mean (1)	SD (2)	Mean (3)	SD (4)	(5)
A. Trial Levels and Quality					
Any Trial	0.080	0.271	0.129	0.336	0.000***
Any Randomized Trial	0.060	0.237	0.095	0.293	0.000***
Any Not Randomized Trial	0.018	0.134	0.023	0.150	0.013**
Any Blinded Trial	0.051	0.221	0.082	0.274	0.000***
Any Not Blinded Trial	0.046	0.209	0.066	0.249	0.000***
Any Comparator Trial	0.051	0.219	0.081	0.274	0.000***
Any No Comparator Trial	0.038	0.191	0.059	0.236	0.000***
B. Technology Novelty and Competition					
Any Trial With Novel Technology	0.055	0.228	0.095	0.293	0.000***
Any Trial With Non-Novel Technology	0.013	0.112	0.017	0.130	0.007***
Firm With High Competition	0.047	0.212	0.078	0.268	0.000***
Firm With Low Competition	0.953	0.212	0.922	0.268	0.000***

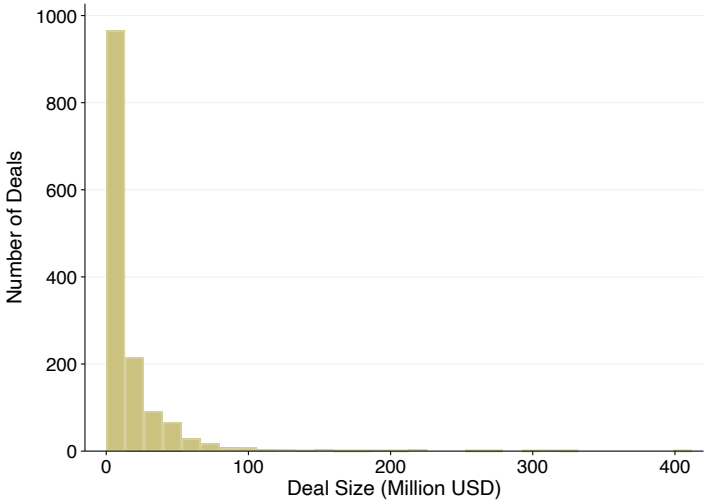
Note: This table presents summary statistics at the startup-year level. The full startup-year sample consists of 26,179 startup-years and 1,843 unique startups. Column 5 presents *p*-values from t-tests comparing the difference of means. *** p<0.01, ** p<0.05, * p<0.1

Figure A1: Timing of Initial VC Investment Across Startups



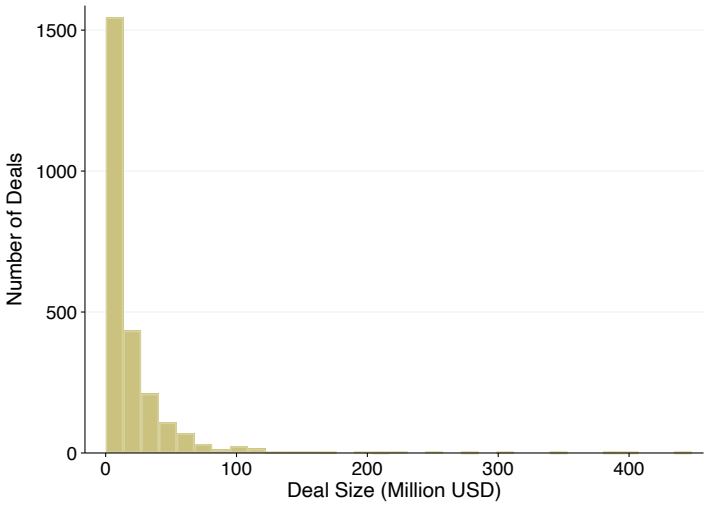
Note: This figure plots the cumulative percentage of startups with VC funding over time.

Figure A2: Distribution of Initial VC Funding Amounts



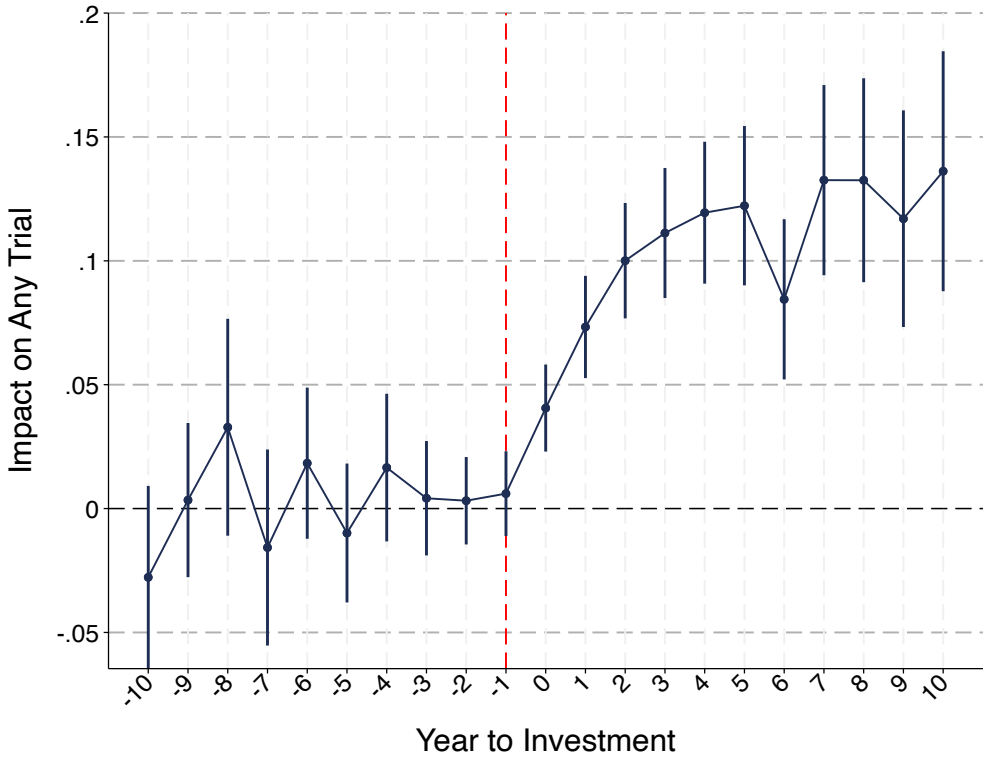
Note: This figure shows the distribution of VC-funded deals initially given to startups. Observations are at the deal-level.

Figure A3: Distribution of All (Initial and Subsequent) VC Funding Amounts



Note: This figure shows the distribution of VC-funded deals, across all (initial and follow-on) deals. Observations are at the deal-level. To ease interpretation, funding amounts are truncated to those less than $500 million USD.

Figure A4: Effect of VC Funding on Any Trial Using Callaway and Sant'Anna (2021) Estimator



Note: This figure presents event study coefficients from the estimation of equation (2) on overall trial investment using the estimator proposed by Callway and Sant'Anna (2021). Shown are coefficients in the 10 years leading and following the initial funding event. Coefficients are estimated from startup-year level OLS regressions. The outcome is an indicator for any trial. Solid vertical lines represent 95% confidence intervals. The dotted vertical line represents the year before the initial funding.

Table A2: Effect of VC Funding on Trial Design Quality Levels

	Dependent Variable: Ln(1 + # Trials)						
	All	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Funded	0.108***	0.0586***	0.0174***	0.0520***	0.0437***	0.0436***	0.0319***
	(0.00739)	(0.00627)	(0.00297)	(0.00571)	(0.00520)	(0.00567)	(0.00464)
Mean of Dep. Var.	0.113	0.077	0.021	0.064	0.059	0.064	0.052
Diff. Wald Test p-value		0.00		0.21		0.05	
Observations	26,179	26,179	26,179	26,179	26,179	26,179	26,179
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality levels. The level of observation is at the startup-year. Column 1 is estimated using OLS. The "Wald Test p-value" is the p-value comparing the $Post \times Funded$ coefficient in columns 2 vs. 3, columns 4 vs. 5, columns 6 vs. 7. Columns 2 to 7 are estimated using seemingly unrelated regressions. Standard errors are clustered at the startup level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Effect of VC Funding on Trial Design Quality, By Technology Novelty

Dependent Variable:	Any Novel Trial		Any Non-Novel Trial		Any Novel Trial		Any Non-Novel Trial		Any Novel Trial		Any Non-Novel Trial	
	Randomized	Not Randomized	Randomized	Not Randomized	Blinded	Not Blinded	Blinded	Not Blinded	Comparator	Not Comparator	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post × Funded	0.0469***	0.0129***	0.00483*	0.00130	0.0401***	0.0315***	0.00525*	0.00273	0.0349***	0.0217***	0.00457*	0.00247
	(0.00514)	(0.00260)	(0.00241)	(0.000926)	(0.00478)	(0.00449)	(0.00214)	(0.00196)	(0.00460)	(0.00398)	(0.00231)	(0.00180)
Mean of Dep. Var.	0.058	0.017	0.011	0.002	0.050	0.045	0.009	0.009	0.049	0.040	0.010	0.007
Diff. Wald Test p-value	0.00		0.11		0.12		0.25		0.01		0.29	
Observations	26,179	26,179	26,179	26,179	26,179	26,179	26,179	26,179	26,179	26,179	26,179	26,179
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality, by technology novelty. The level of observation is at the startup-year. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. The "Wald Test p-value" is the p-value comparing the $Post \times Funded$ coefficient in columns 1 vs. 2, columns 3 vs. 4, columns 5 vs. 6, columns 7 vs. 8, columns 9 vs. 10, columns 11 vs. 12. All regressions are estimated using seemingly unrelated regressions. Controls include startup fixed effects and year fixed effects. Standard errors are clustered at the startup level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Effect of VC Funding on Trial Design Quality, Before and After 2016

	Dependent Variable: Any Trial					
	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)
A. Before 2016						
Post × Funded	0.0585***	0.0108**	0.0512***	0.0235***	0.0378***	0.00854
	(0.00847)	(0.00403)	(0.00789)	(0.00685)	(0.00781)	(0.00614)
Mean of Dep. Var.	0.093	0.024	0.080	0.062	0.077	0.051
Diff. Wald Test p-value	0.00		0.00		0.00	
Observations	15,556	15,556	15,556	15,556	15,556	15,556
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
B. On/After 2016						
Post × Funded	0.0898***	0.0185**	0.0755***	0.0563***	0.0843***	0.0488***
	(0.0126)	(0.00662)	(0.0124)	(0.0110)	(0.0126)	(0.0104)
Mean of Dep. Var.	0.068	0.017	0.059	0.056	0.063	0.053
Diff. Wald Test p-value	0.00		0.26		0.03	
Observations	10,623	10,623	10,623	10,623	10,623	10,623
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality. Panel A examines the effect of VC funding before 2016. Panel B examines the effect of VC funding on/after 2016. The level of observation is at the startup-year. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. The "Wald Test p-value" is the p-value comparing the $Post \times Funded$ coefficient in columns 1 vs. 2, columns 3 vs. 4, columns 5 vs. 6. All are estimated using seemingly unrelated regressions with startup fixed effects, year fixed effects, and disease fixed effects. Standard errors are clustered at the startup level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Effect of VC Funding on Trial Design Quality, Startup-Disease-Year Analysis

	Dependent Variable: Any Trial					
	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)
A. Narrow Disease Category (ICD9)						
Post × Funded	0.000151***	0.0000480***	0.000140***	0.0000994***	0.000100***	0.0000522***
	(0.0000142)	(0.00000793)	(0.0000126)	(0.0000135)	(0.0000127)	(0.0000125)
Mean of Dep. Var.	0.0003	0.0001	0.0002	0.0003	0.0002	0.0003
Diff. Wald Test p-value	0.0000		0.0173		0.0019	
Observations	13,979,586	13,979,586	13,979,586	13,979,586	13,979,586	13,979,586
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Disease FEs	Yes	Yes	Yes	Yes	Yes	Yes
B. Broad Disease Category (ICD9 Chapters)						
Post × Funded	0.00478***	0.00117***	0.00419***	0.00262***	0.00344***	0.00174***
	(0.000400)	(0.000162)	(0.000370)	(0.000308)	(0.000363)	(0.000274)
Mean of Dep. Var.	0.0065	0.0014	0.0055	0.0044	0.0054	0.0037
Diff. Wald Test p-value	0.0000		0.0002		0.0000	
Observations	471,222	471,222	471,222	471,222	471,222	471,222
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Disease FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality, using a startup-disease-year analysis. Panel A measures diseases at the ICD9 level. Panel A measures diseases at the ICD9 chapter level. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. The "Wald Test p-value" is the p-value comparing the *Post* × *Funded* coefficient in columns 1 vs. 2, columns 3 vs. 4, columns 5 vs. 6. All are estimated using seemingly unrelated regressions with startup fixed effects, year fixed effects, and disease fixed effects. Standard errors are clustered at the startup level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Effect of VC Funding on Trial Design Quality, by Startup Age

	Dependent Variable: Any Trial					
	Randomized	Not Randomized	Blinded	Not Blinded	Comparator	Not Comparator
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Funded × Old Firm	-0.0122	-0.00636	-0.00662	-0.00726	-0.00657	-0.0109
	(0.00972)	(0.00531)	(0.00932)	(0.00851)	(0.00940)	(0.00830)
Post × Funded	0.0856***	0.0219***	0.0720***	0.0489***	0.0655***	0.0397***
	(0.00801)	(0.00485)	(0.00771)	(0.00706)	(0.00761)	(0.00690)
Mean of Dep. Var.	0.0830	0.0213	0.0716	0.0593	0.0710	0.0520
Observations	26,179	26,179	26,179	26,179	26,179	26,179
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports DID estimates of the effect of VC funding on clinical trial design quality, by startup age. The level of observation is at the startup-year. The outcome variable switches from 0 to 1 if a clinical trial with a specific design characteristic is reported in a startup-year. For a given startup-year observation, $OldFirm$ is equal to one if the startup's age in the year it receives funding is greater than the median age (2 years) of all funded startups in the years they receive funding. Controls include startup fixed effects and year fixed effects. Estimates are from OLS regressions. Standard errors are clustered at the startup level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.