Financing Experimentation

Xuelin Li and Tong Liu*

August 2026

Abstract

How do innovative firms time external financing as experimentation reveals project quality and entrepreneurial ability? Using U.S. biotech drug-development and IPO data, we document IPO firms with late development stages have higher subsequent drug-approval rates, even for projects initiated after listing. Motivated by this persistence, we structurally estimate a dynamic model with private information about entrepreneurial ability, public learning about ability and project quality through experimentation, and time-varying market conditions. High-ability entrepreneurs delay financing to reduce underpricing, but waiting exposes projects to liquidation risk. Adverse selection reduces ex ante project value by 4.9%, and the loss falls almost entirely on high-ability entrepreneurs. Counterfactuals show that shortening development and weakening evidentiary standards have sharply different effects: removing one required trial milestone raises high-ability value by 26.6%, while making trials 10% less informative lowers it by 3.4%.

JEL: D82, D83, G32, O31, L26, L65, C51

Keywords: Financing experimentation, adverse selection, IPO timing, public learning, entrepreneurial ability, drug development, structural estimation

*Li: Columbia Business School, xuelin.li@columbia.edu; Liu: MIT Sloan School of Management, tongl@mit.edu. We thank Viktar Fedaseyeu, Thomas Geelen, Itay Goldstein, Li He, Enrique Schroth, Luke Taylor, and seminar and conference participants at The Wharton School, EFA Annual Meeting, CICF, 3rd COAP Conference for valuable comments and discussions. We thank Yuxuan Zheng for excellent research assistance. Liu gratefully acknowledges support from the MIT Wade Fund. All errors and omissions are our own.

1 Introduction

Financing innovative technology is a central challenge for entrepreneurs. Novel technologies require sustained experimentation before generating cash flows, and neither entrepreneurs nor investors initially know whether a project will succeed. This technological uncertainty is compounded by uncertainty about the entrepreneur's scientific and organizational ability, which shapes her capacity to select and advance promising projects. Because the entrepreneur has better information about this ability than outside investors, investors thus face common uncertainty about project quality alongside adverse selection about entrepreneurial ability. Experimentation gradually resolves both: outcomes reveal information about the project while building a public record of the entrepreneur's ability. This creates a dynamic financing dilemma (Kerr et al., 2014). Raising capital early reduces liquidation risk but may force a high-ability entrepreneur to accept a low valuation. Waiting for further evidence mitigates adverse selection but requires costly experimentation and prolongs exposure to liquidation. Motivated by this dynamic, we study two questions. First, how does the interaction of technological uncertainty and adverse selection shape external financing during experimentation? Second, what are the efficiency implications of information frictions in the market?

We address these questions by structurally estimating a dynamic model of financing through experimentation, in which entrepreneurs with heterogeneous, privately known ability seek external financing for novel R&D projects of unknown quality. The key innovation of the model is that costly experimentation jointly resolves uncertainty about project quality and adverse selection about entrepreneurial ability, while delaying financing exposes projects to liquidation risk. We bring the model to data on the initial public offering (IPO) decisions of biotech startups. IPOs provide a natural setting for our analysis: they are a key financing decision for startups and central to broader changes in U.S. public markets. Existing work documents a decline in the number of listed firms, a shift toward IPOs at later stages of firm development (e.g. Gao et al., 2013; Doidge et al., 2017; Ewens and Farre-Mensa, 2020), and a growing concentration of new listings in high-technology sectors, where firms often lack stable revenues and fully proven products (Celentano and Rempel, 2026). The key contribution of our empirical exercise is to quantify the role of informational frictions in explaining the listing gap and other changing patterns in U.S. public markets, as well as the resulting efficiency losses.

This estimation requires an empirical setting in which information frictions are severe ex ante but can be partially resolved through a sequence of publicly observed experimentation outcomes. The biotech sector provides such an ideal setting. This setting is important, as new drug development accounts for over 10 percent of aggregate U.S. R&D spending (Benmelech et al., 2021). Also, drug development is a canonical process of learning through experimentation, as the efficacy and safety of drug candidates are revealed through a standardized, publicly observed sequence of clinical milestones. We assemble a new data set combining detailed drug-development histories of U.S.-based companies with their IPO records, allowing us to link the public learning process generated by these trial milestones to firms' financing decisions.

With the data, several descriptive patterns discipline the model. Biotech firms go public at

very different points in their drug development process: 25.5% list before any clinical trials begin, while the modal IPO occurs in Phase II trial. The development stage at IPO also appears to reveal persistent entrepreneurial ability. Project outcomes are correlated across drugs within the same firm, and new projects initiated post-IPO by late-stage IPO firms (Phase III or later) have approval probabilities 10.8% higher than those initiated by earlier-stage IPO firms. Because these subsequent projects are different drugs, this evidence suggests that the development stage at IPO reveals an entrepreneur's persistent ability to generate successful projects, distinct from the quality of any individual drug.

Firm liquidation, by contrast, is largely unrelated to its own project-specific experimentation news. Nearly 70% of liquidated firms had no prior pipeline failure, and recent project failures explain little of liquidation. Meanwhile, higher biotech-sector price-to-sales ratios raise firms' quarterly IPO probabilities but do not predict liquidation or drug failure. Thus, private firms are forced to liquidate even without adverse experimental news, while favorable public valuations encourage firms to go public. The model captures these patterns through liquidation risk and time-varying public-market valuations.

Formally, we develop a dynamic model of IPO timing during experimentation. A drug project advances through a sequence of publicly observed development milestones. In each period, the entrepreneur chooses whether to remain privately financed or go public. Remaining private allows experimentation to continue but requires paying development costs and exposes the project to a liquidation shock. An IPO transfers the project's cash-flow claims to deep-pocketed public investors, who continue development without this liquidity risk. The competitive IPO price reflects the project's development stage, prevailing market valuations, and investors' beliefs.

The first distinctive feature is that the model separates persistent entrepreneur ability from project-level uncertainty. The entrepreneur privately observes whether her ability is high or low, but project quality is initially unknown to everyone. Ability shifts the probability of drawing a good project without determining whether any particular project succeeds. Investors learn about both project quality and entrepreneur ability as bad projects oftentimes fail experimentation. Milestone advancement is good news about type as high-ability entrepreneurs are more likely to have good projects. The financing decision is informative as well because the two types follow different IPO strategies. Experimentation therefore reduces uncertainty about the project directly and adverse selection about the entrepreneur indirectly.

The second distinctive feature is that the equilibrium financing cutoff arises in public-market valuations. For a given development stage and public belief, the high type waits when valuations are low and finances when they are high. Waiting avoids selling at a price that pools her with the low type, but high valuations increase the project value exposed to liquidation and eventually induce her to go public despite underpricing. The low type finances whenever the high type does and may also finance at lower valuations while the high type waits. In this separating region, the low type may mix between financing immediately and waiting for a future pooling opportunity. Market valuations can therefore generate three ordered regions: both types wait, the high type

waits while the low type may finance, and both types finance. In the equilibrium, low types account disproportionately for early IPOs, whereas high types tend to wait for informative milestones and finance later. This sorting helps explain IPOs at both early and advanced stages and exposes high-ability entrepreneurs to greater liquidation risk.

We estimate the model by simulated method of moments (SMM), matching IPO valuations, the distribution of development stages at IPO, private-firm liquidation hazards, and drug progression. The estimated parameters deliver two central implications. First, adverse selection is severe. A high-type entrepreneur is nearly seven times as likely as a low-type entrepreneur to draw a good project, but investors' prior probability of facing a high type is only about 46%, leaving substantial uncertainty about project quality. Second, experimentation is highly informative: conditional on a development outcome, a bad project fails with probability about six out of seven. Together, these estimates imply that early financing is costly for a high type because it forgoes informative signals that would reduce initial underpricing. Waiting, however, is also costly. The estimated liquidation hazard is modest in any quarter but accumulates over the long development process, exposing high types to disproportionate liquidation risk.

To quantify the cost of this trade-off, we compare expected firm values with a symmetric-information benchmark in which entrepreneur type is observable. We decompose the value gap into mispricing, the value difference realized when financing occurs under imperfect investor beliefs, and liquidation, the value lost when the project is destroyed before financing. Asymmetric information reduces ex-ante project value by 4.9%. The loss is concentrated on high-ability entrepreneurs, whose value falls by 5.2%; About 85.2% of this decline comes from mispricing and 14.8% from liquidation. For low-ability entrepreneurs, the gain from mispricing and the loss from liquidation are both small and nearly offset. Thus, the value loss falls almost entirely on high-ability entrepreneurs, who undertake more experimentation in equilibrium.

Counterfactual analysis of the estimated model has implications for current policy debates over how to ease the burden of drug R&D, either by reducing the number of development stages or by relaxing the evidentiary standards within each phase. The model shows that these reforms are not equivalent. Reducing the number of required milestones from six to five, while preserving the informativeness of the remaining milestones, raises equilibrium value by about 29% and high-type value by 26.6%. Almost all of this gain comes from higher underlying project value; mispricing and liquidation change little. By contrast, reducing by 10% the probability that a bad project fails conditional on a development outcome lowers high-type value by 3.4%. Less informative milestones slow investor learning, keep high types pooled with low types for longer, and increase mispricing. Shortening the development process can therefore raise value substantially, whereas weakening its information content can lower value.

We also use the model to study changes in the cost intensity of development, motivated by the rise in R&D and clinical-trial costs (Sertkaya et al., 2024). Higher costs could, in principle, improve selection by discouraging low-quality projects from continuing. Our counterfactual suggests that this screening channel is weak. A 10% increase in flow R&D costs lowers high-type value by 3.6%.

Almost all of this decline comes from lower underlying project value, with little change in mispricing or liquidation. Higher development costs reduce the profitability of experimentation but do not make milestone outcomes more informative. They therefore lower value mainly through a real-cost channel rather than by materially changing financing strategies or mitigating adverse selection.

Our paper is closely related to the dynamic adverse-selection literature, in which privately informed sellers delay trade while public information resolves asymmetric information (Daley and Green, 2012, 2016). More broadly, our paper relates to signaling models in which privately informed agents time financing, investment, or reallocation to avoid pooling with lower-quality agents (e.g. Grenadier and Malenko, 2011; Morellec and Schürhoff, 2011; Fuchs et al., 2016). We contribute to this literature in two ways. First, we endogenize public information through experimentation. Milestones reveal entrepreneur type and generate the familiar skimming property: low types experiment less and finance earlier, while high types delay financing. But successful milestones also narrow type-contingent project-quality beliefs, making type less relevant for pricing. Experimentation therefore changes both investors' posterior over type and the severity of type-based adverse selection.[1] Second, we separate the information state from the market-valuation state. This distinction matters empirically because entrepreneurial financing reflects both development-stage variation and public-market valuation cycles.[2] It also matters theoretically because the two states affect financing incentives differently: low beliefs tend to induce low-type exit, whereas low valuations make financing unattractive for both types.

Our paper is also related to theoretical and empirical work on information frictions in the IPO process. Bustamante (2012) studies how IPO timing can signal firm quality. Other IPO models emphasize public-market information production and information externalities across offerings (e.g. Chemmanur and Fulghieri, 1999; Subrahmanyam and Titman, 1999; Benveniste et al., 2002). Empirically, a related IPO literature studies how issuer uncertainty and information production affect IPO pricing, volatility, and waves (Lowry and Schwert, 2002; Lowry et al., 2010; Hanley and Hoberg, 2010; Loughran and McDonald, 2013).[3] We differ by modeling and quantifying how pre-IPO strategic experimentation reduces project uncertainty and adverse selection before the IPO process begins. This connects entrepreneurial learning in IPO timing (Pástor et al., 2009) with investor-side information frictions in listing choice (Celentano and Rempel, 2026). Our quantitative approach also relates to structural work on adverse-selection and agency frictions (e.g. Guo et al., 2025; Nikolov et al., 2021; Celik et al., 2022; Feng et al., 2026). The distinctive feature is that costly experimentation produces public information before an IPO, shaping both financing timing and exposure to liquidation risk.

[1] Close to our learning mechanism, Strebulaev et al. (2016) study issuance timing when cash-flow news both reveals firm quality and reduces the need for external financing. Experimentation differs because milestone news also changes the severity of adverse selection.

[2] Relatedly, Yung et al. (2008) and Zryumov (2015) link IPO waves to cyclical changes in the composition of firms seeking public financing under adverse selection, but without experimentation.

[3] IPO pricing has also been studied as a broader information-friction problem, including frictions between informed and uninformed investors, certification by intermediaries, and information extraction through bookbuilding (e.g. Carter and Manaster, 1990; Megginson and Weiss, 1991; Michaely and Shaw, 1994; Cornelli and Goldreich, 2003).

Our paper speaks to the literature on financing innovation. R&D is intangible, its payoffs arrive late and are highly skewed, and the innovator knows more about the project than outside investors do, which pushes innovative firms toward equity and raises their cost of external capital (Hall and Lerner, 2010; Bryan and Williams, 2021).[4] Biotech makes the dependence on equity visible, as firms turn to alliances when public equity markets are cold (Lerner et al., 2003; Robinson and Stuart, 2007). The friction is largest in drug development, where experimentation is long, expensive, and publicly observed (Lo and Thakor, 2022). Existing work shows that drug innovation is distorted by financial, institutional, and market frictions, including risk aversion (Krieger et al., 2022a), patent protection (Budish et al., 2015), over commitment (Guenzel and Liu, 2026), and M&A incentives (Phillips and Zhdanov, 2013; Cunningham et al., 2021; Krieger et al., 2022b). Within private markets, Li et al. (2023) study how common ownership shapes innovation targets, Li et al. (2024) investigate how VCs prioritize drug projects within their portfolios, and Aghamolla and Thakor (2022) examine how private firms respond to competitors' IPOs by seeking external financing. We focus on a different friction: asymmetric information between entrepreneurs and outside investors before IPO, and we uniquely bring the drug development data to model and quantify how costly experimentation resolves this friction while exposing firms to liquidation risk.

2 Data

We focus on the biotechnology industry, particularly firms whose primary activity is the discovery and development of new drug candidates, rather than generic manufacturing, wholesale distribution, or medical equipment. In this section, we first describe the institutional setting, including how drug experimentation proceeds, how it is financed, and how information frictions arise along the way, and then detail the datasets we used in the analysis.

2.1 Institutional background

Drug development as a sequence of experiments Bringing a new therapy to market is a long, staged, and highly uncertain process. A drug candidate must clear a predefined sequence of milestones before it can be commercialized: discovery and preclinical work, three phases of human clinical trials (Phase I, II, and III), pre-registration, registration, and finally launch. Each stage is designed to resolve a specific source of uncertainty. Preclinical work screens a molecule for basic safety and biological activity; Phase I tests safety, dosing, and tolerability in a small group of human subjects; Phase II evaluates efficacy and side effects in patients with the target condition; and Phase III confirms efficacy in large, statistically powered trials before the firm seeks regulatory approval. Because these milestones must be passed in order, development is naturally modeled as the gradual resolution of a project's underlying quality through costly experimentation: each completed stage is an experiment whose outcome, such as advance or fail.

[4]The experimentation view of entrepreneurship sharpens the problem: startups finance a sequence of costly experiments, and the cost of running them shapes which ideas get financed and on what terms (Kerr et al., 2014; Ewens et al., 2018).

This process is slow, expensive, and overwhelmingly likely to end in failure. The full path from discovery to approval typically spans about a decade, and the total cost of bringing a new drug to market frequently exceeds $1 billion (DiMasi et al., 2003, 2016). The vast majority of programs never reach the market. A candidate can be discontinued at any stage. Firms also frequently shelve programs quietly rather than formally terminating them, creating so-called "zombie" projects that linger without progress. These features mean that, at any point before approval, an entrepreneur holds an asset with large potential upside, substantial uncertainty, and quality that is revealed only gradually through additional costly trials.

Financing experimentation Because revenues arrive only after launch, if ever, biotech firms must fund long periods of experimentation before any product generates cash flow. A young biotech typically has little or no revenue, accounting losses, high R&D spending, and few pledgeable assets. Its value comes primarily from intangible drug candidates whose quality is difficult to verify. Financing therefore comes largely from equity. In the private phase, venture capital investors fund successive rounds tied to scientific and clinical progress. As development proceeds, the firm may also raise capital from public investors through an IPO, which provides access to a more liquid capital market but prices the firm under a prevailing valuation sentiment. Public-market appetite for biotech is highly cyclical: "hot" windows in which valuations and issuance surge alternate with "cold" periods in which public financing becomes scarce. The decision of when to go public is therefore inseparable from the decision of how much experimentation to undertake while private.

This financing choice involves a fundamental trade-off. Remaining private and running another trial allows the entrepreneur to generate additional information about the drug's quality, but delay is risky because the firm may be unable to finance continuation before the next milestone is reached. Going public provides capital and locks in a valuation, but it requires the entrepreneur to sell claims on the project before uncertainty is fully resolved, at a price set by outside investors who cannot perfectly infer the entrepreneur's type or the project's prospects. This tension between learning, liquidation risk, and mispricing is the central economic force the paper quantifies.

Information frictions Investors funding a novel technology face two distinct information problems. The first concerns the entrepreneur, or the "jockey"; the second concerns the project, or the "horse." This distinction is central in the entrepreneurial finance literature (Kaplan et al., 2009; Gompers et al., 2020). In our setting, the jockey problem creates adverse selection. Founders differ in scientific judgment, technical expertise, and ability to select promising projects, but these traits are difficult for outside investors to verify ex ante. This difficulty is stark in life sciences. At one end are renowned scientific founders such as Harvey Lodish, a leading MIT and Whitehead Institute scientist and a founder or scientific advisor of pioneering biotechnology companies including Genzyme and Millennium Pharmaceuticals. At the other end are founders whose claimed scientific capabilities later prove unreliable or fraudulent, as in the case of Elizabeth Holmes at Theranos. Founder-level and organizational choices shape drug-development outcomes (Guedj and Scharfstein, 2004; Budish et al., 2015), and managerial ability more broadly is persistent, only partially

observable, and priced by financial markets (Kaplan and Sorensen, 2021; Cziraki and Jenter, 2022). The model captures this adverse selection problem by assuming that entrepreneurs privately know their own type, while investors do not.

The horse problem is different. It represents common uncertainty about the viability of a novel drug candidate. Even conditional on the entrepreneur's ability, neither investors nor the entrepreneur directly observes a candidate's efficacy and safety without experimentation. Most clinical assets fail, and ex ante success probabilities are difficult to assess even for expert teams. As a result, quality is revealed only gradually through the clinical trial process itself (Wong et al., 2019). Rubius Therapeutics illustrates this project-level uncertainty. The company was launched around advances in red-cell biology associated with Lodish and raised substantial capital to develop an engineered red-cell therapeutic platform. It later discontinued its clinical trials and restructured after early clinical evidence failed to justify continued investment in those candidates.[5] Thus, exceptional founder ability can shift the distribution of project quality, but it does not resolve uncertainty about the biological quality of any particular project.

2.2 Data and sample construction

Drug development data We focus on biotechnology and pharmaceutical firms headquartered in the U.S. The drug development data come from Cortellis Competitive Intelligence and allow us to observe, for each drug candidate, its developer ID and name, the set of indications it targets,[6] and its recorded development status history, from discovery, preclinical, Phase I, Phase II, Phase III, pre-registration, and registration to launch,[7] together with the dates on which each status is recorded. The records are observed at the drug-by-indication level. We aggregate these observations to the drug level by assigning each drug its most advanced development status across all indications in a given quarter and then construct a quarterly firm-by-drug panel. Within each firm's pipeline, we focus on its lead drug, defined as the active drug that attains the highest stage of development by the end of the sample period. In the event that multiple drugs reach the same highest development stage, we designate as the lead drug the one with the longest development history. All firm-level analyses are conducted at the firm-by-lead-drug level.

To identify the outcome of a drug, we track its development status over time. We classify a drug as suspended at a given phase if it is explicitly coded as suspended, discontinued, or withdrawn, or coded as "no development reported" for over four consecutive years (Li et al., 2023). A firm's

[5] See "Rubius Therapeutics Announces Strategic Update" (2022) for further details: https://www.rubiustx.com/ir-sub/news-releases/news-release-details/rubius-therapeutics-announces-strategic-update/.

[6] An indication represents the type of disease a drug targets. We map each drug indication to the ninth revision of the International Classification of Diseases (ICD-9) using the Cortellis indication-to-ICD-9 crosswalk of Li et al. (2023). The crosswalk is hierarchical, running from 559 three-digit codes, to 117 second-level therapeutic categories, to 18 top-level chapters. Our empirical specifications use the second-level categories throughout, which is also the level at which we project drug sales in Online Appendix A.1; we use the 18 chapters only for the aggregate therapeutic-area breakdown reported in Table 1, where the finer partition would not be legible. We sometimes refer to these simply as ICD-9 categories or ICD codes for conciseness.

[7] Pre-registration refers to the period after pivotal clinical development and before formal regulatory review; registration refers to the period in which a marketing application is under regulatory review.

lead drug is classified as having advanced if it reaches a strictly higher development phase in a subsequent quarter.

Biotech IPO sample To construct the sample of publicly traded biotechnology and pharmaceutical firms, we begin from the merged CRSP-Compustat universe over 1990–2022 and retain firms whose GICS sub-industry, NAICS, or SIC codes place them in biotechnology, pharmaceutical preparations, biological products, in-vitro diagnostics, or commercial biological research, following the industry classification in Thakor et al. (2017).[8] We manually verify each firm's IPO date against SEC filings, match each firm to its CRSP permanent number, CUSIP, and ticker, and remove false positives whose industry codes match but that are not in-scope drug developers. We then merge the IPO firms with their Cortellis drug development histories.

Firm valuation and market conditions We measure each firm's public-market valuation at IPO using its equity market capitalization in the IPO quarter, calculated from CRSP as share price times shares outstanding and converted to 2023 dollars using the GDP deflator. We use post-listing market capitalization rather than offer-price valuation because offer prices are missing for some firms and may reflect strategic underpricing, underwriting frictions, or allocation incentives. The post-listing market capitalization better captures the public market's assessment of the firm in a liquid market. For the structural estimation in Section 5, we scale this valuation by the lead drug's projected average annual sales if successfully launched. We construct projected sales using Cortellis realized and predicted worldwide drug sales and EvaluatePharma analyst forecasts; Appendix A.1 describes the procedure in detail. The resulting sales-normalized valuation multiple is winsorized at the 1st and 99th percentiles. To capture time variation in public-market sentiment toward the sector, we use the quarterly price-to-sales ratio of the NYSE Arca Biotechnology Index (BTK), obtained from Bloomberg, from 1993 to 2023. We treat this series as the aggregate market-condition state in the structural model.

Exit outcomes We track four exit or transfer events for each firm: IPO, acquisition, out-licensing, and bankruptcy or liquidation. An IPO is dated from the verified offering date described above. Mergers and acquisitions are identified from Thomson Reuters SDC Platinum and matched to our firms. Out-licensing events are identified from the Cortellis development records. Bankruptcies and liquidations are identified from PitchBook, supplemented by hand-collected bankruptcy filing dates. A firm's panel begins in the earliest quarter for which Cortellis records a development update for its lead drug and ends in the first quarter in which any exit or transfer event occurs, or at the end of the sample period if no such event occurs.[9]

[8] Specifically, we keep firms with GICS sub-industry codes 35201010 (Biotechnology) or 35202010 (Pharmaceuticals); NAICS codes 325411 to 325414, 424210, or 541710 to 541711; or SIC codes 2833 to 2836, 5122, or 8731.

[9] These event types are typically mutually exclusive. In the rare cases in which multiple event types occur in the same quarter, we assign the panel end date to that quarter.

Data filters We apply several filters to construct our main analysis sample. First, we restrict attention to U.S.-headquartered firms classified as operating companies, excluding universities, hospitals, and research institutes. Second, we truncate the panel at the fourth quarter of 2020, because the Cortellis development snapshot has essentially no coverage thereafter. Third, for IPO firms, we require non-missing IPO valuation, which restricts the IPO subsample to firms that can be linked to CRSP. These filters yield a panel of 5,736 firms observed over 1993–2020, of which 668 complete an IPO during the sample period and 5,068 do not go public during the sample period.

2.3 Summary statistics

Table 1 reports summary statistics for the analysis sample. Panel A describes the cross-section of firms; Panel B describes the firm-quarter panel. Of the 5,736 firms in the sample, 11.6% complete an IPO during the sample window and 6.6% are liquidated or go bankrupt, so the typical biotech in our data neither goes public nor fails within the observation window. Conditional on going public, the median firm reaches its IPO twelve quarters (three years) after first appearing in the data, carries a median of four active drug projects, and lists with a lead drug in early clinical development (median lead-drug stage of Phase II). Thus, public equity financing often occurs while the firm's main asset remains far from approval and before substantial uncertainty about the lead drug has been resolved. The market capitalization at IPO has a median of \$0.3 billion and a mean of \$0.7 billion, reflecting a right-skewed distribution of public-market valuations. The lead-drug indications of IPO firms concentrate in oncology (27.8%), nervous-system (13.5%), and endocrine-metabolic (10.3%) diseases, and the firms cluster in the established biotechnology hubs of California (30.5%), Massachusetts (23.6%), and New Jersey (6.6%). Panel B shows that, across all firm-quarters, the median firm is 20 quarters old, holds one active drug project, and advances its lead drug to a higher development phase in only 1.7% of quarters. These facts underscore the slow, infrequent arrival of information that resolves uncertainty about drug quality.

Panel (a) of Figure 1 shows that biotech firms often go public before the uncertainty about their drugs has been fully resolved. The modal IPO firm has a lead drug in Phase II, but a large share lists even earlier: 25.5% go public at the preclinical stage and 15.7% at Phase I. Thus, 41.2% of IPO firms enter public markets before their lead drug has produced Phase II evidence on efficacy. By contrast, relatively few firms wait until after Phase III, when the drug has completed the main clinical sequence and both project quality and entrepreneurial ability are more fully revealed. This pattern is consistent with the central trade-off in our model, as entrepreneurs with different abilities have different incentives to experiment.

Panel (b) of Figure 1 plots the annual count of biotech IPOs in our sample against the annual mean BTK price-to-sales ratio from 1993 to 2020. IPO activity is elevated during several high-valuation periods, including the 1999–2000 and 2014 episodes, consistent with public-market conditions affecting the timing of listings. The relationship is not one-to-one. The record IPO volume in 2020 occurs after the BTK ratio had declined from its 2014 peak, suggesting that other forces, including the surge in investor interest in biotechnology during the COVID-19 pandemic,

Table 1: Summary Statistics

This table reports summary statistics for the analysis sample of U.S. biotech firms with drug-development records in Cortellis. Panel A reports firm-level statistics. The first block reports exit outcomes for the full sample. The second block reports at-IPO characteristics for IPO firms with non-missing CRSP valuation: firm age in quarters from first sample appearance to IPO, number of active drug projects, lead-drug development stage on a 0–6 scale from preclinical to launch, contemporaneous BTK biotechnology price-to-sales index, and IPO valuation, defined as equity market capitalization in the IPO quarter converted to 2023 dollars using the GDP deflator. The third and fourth blocks report the top three therapeutic areas, based on lead-drug indications mapped to ICD-9 chapters, and the top three U.S. headquarters states among IPO firms. Panel B reports firm-quarter statistics for the quarterly panel. Variable-specific observation counts differ when the relevant measure is not observed in every firm-quarter.

Panel A: Firm-level statistics

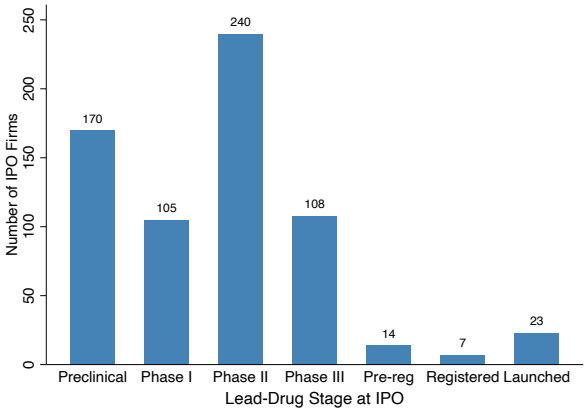
	N	Mean	SD	P25	Median	P75
Exit outcomes (full sample)						
IPO firm	5,736	0.116	0.321	0.000	0.000	0.000
Liquidated/bankrupt	5,736	0.066	0.248	0.000	0.000	0.000
At-IPO snapshot (IPO firms only)						
Firm age at IPO (qtrs)	668	15.6	13.9	5.0	12.0	22.0
Number of drug projects at IPO	668	5.07	5.45	2.00	4.00	7.00
Lead-drug stage at IPO (0–6)	668	1.71	1.41	0.00	2.00	2.00
BTK P/S ratio at IPO	668	7.68	2.64	6.39	7.31	8.90
IPO valuation (2023 $B)	668	0.7	3.2	0.1	0.3	0.7
Top therapeutic areas (lead-drug indication, IPO firms)						
Neoplasms (Oncology)			27.8%			
Nervous/Sense Organs			13.5%			
Endocrine/Metabolic			10.3%			
Top US states of headquarters (IPO firms)						
California			30.5%			
Massachusetts			23.6%			
New Jersey			6.6%			

Panel B: Firm-quarter statistics

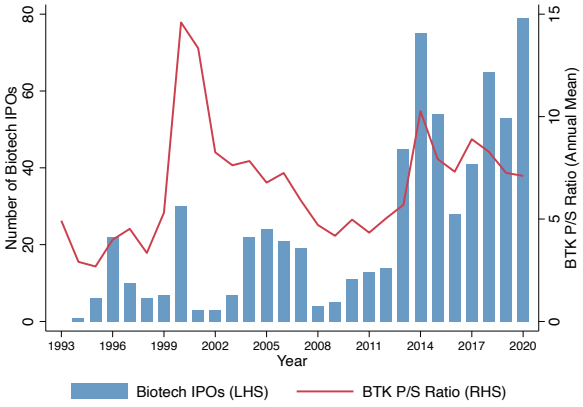
	N	Mean	SD	P25	Median	P75
Firm age (qtrs)	173,064	25.68	21.49	9.00	20.00	37.00
Lead-drug age (qtrs)	173,064	25.71	21.52	9.00	20.00	37.00
Number of drug projects	173,064	3.19	8.88	1.00	1.00	3.00
of which: early stage (Preclin/P1)	173,064	2.61	6.98	1.00	1.00	3.00
of which: late stage (P2+)	173,064	0.58	2.30	0.00	0.00	1.00
Lead-drug stage (current, 0–6)	173,058	1.05	1.48	0.00	0.00	2.00
Lead-drug milestone-move this qtr	173,060	0.017	0.127	0.000	0.000	0.000
IPO this qtr	173,064	0.004	0.060	0.000	0.000	0.000
BTK P/S ratio	173,064	7.07	2.17	5.23	7.04	8.62
Bankruptcy this qtr	173,064	0.002	0.047	0.000	0.000	0.000

Figure 1: IPO Timing and Market Conditions

Panel (a) plots the distribution of lead-drug development stages at the IPO date for biotech IPO firms in the analysis sample. Panel (b) plots the annual count of biotech IPOs in our sample (left axis) against the annual mean BTK price-to-sales ratio (right axis) from 1993 to 2020. Lead-drug stages are measured from Cortellis development records; IPO dates are manually verified against SEC filings.



(a) Lead-drug stage at IPO



(b) IPO counts and market conditions

also contributed to that year's issuance. The figure motivates treating aggregate biotech-market valuations as an important, but not exclusive, state variable in the IPO decision.

3 Reduced-Form Evidence

The model developed in Section 4 rests on four key ingredients: entrepreneurs differ in a persistent, privately known ability that is distinct from the quality of any particular project; firms that remain private face a liquidation risk that destroys the asset; public-market valuation sentiments affect the chance of firms to go public, but not liquidation or drug-failure hazards; and, consistent with adverse selection, the development stage of the lead drug at IPO is informative about entrepreneurial ability. This section documents evidence for each of these features directly in the data, before imposing any structural assumptions. The evidence is not intended to identify the model's parameters, which is the task of Section 5. Rather, its purpose is to establish that the economic forces formalized by the model are present in the data and to discipline the modeling choices that follow.

3.1 Distinct between entrepreneurial ability and project quality

The jockey and horse in Section 2 are distinct only if entrepreneurial ability differs from the latent quality of any particular molecule. Ability shifts the distribution of project quality but does not determine a given project's success. This distinction is testable: if drug development has a persistent firm-level component, separate molecules developed by the same firm should have correlated outcomes beyond chance.

Table 2 conducts this project-level test for both public and private firms. The sample includes projects initiated by 2015, providing at least five years of development records before the data end in 2020; columns (5)–(7) impose further restrictions described below. A project succeeds if it is launched or registered by the end of the sample. Among firms with at least two projects, we regress each project's success on the mean success rate of the firm's other projects. This leave-one-out measure avoids a mechanical correlation between the outcome and regressor. Standard errors are clustered by firm.

The association is large. Across 22,545 projects at 2,755 multi-project firms, the unconditional success rate is 8.3%, compared with 2.5% when no sibling project succeeds and 50.6% among the projects whose siblings all succeed. Column (1) reports an uncontrolled coefficient of 0.656. This estimate may overstate the ability channel because firms differ in operating period, therapeutic specialization, and projects' pipeline-entry stages, all of which can correlate outcomes within firms. Columns (2)–(4) cumulatively add initiation-year-quarter, ICD-9 category, and entry-stage fixed effects. The coefficient declines to 0.637, 0.605, and 0.279, respectively, but remains positive and significant at the 1% level throughout.

Columns (5)–(7) retain the controls in column (4) but vary the comparison. Column (5) computes the leave-one-out mean using sibling projects initiated within five years before or after the focal project, making the comparison contemporaneous. To exclude correlations generated by post-IPO resources rather than founder ability, column (6) retains only projects initiated while the firm was private, and column (7) retains only firms that never listed. The respective coefficients are 0.260, 0.263, and 0.292. The firm-level component is thus not an artifact of public-market financing and is, if anything, strongest among firms that never list. At the same time, the association is far from one-to-one. In the most controlled full-sample specification, the coefficient is 0.279, and the largest adjusted R^2 in the table is 0.437. Thus, sibling-project outcomes contain information about persistent firm-level ability, but substantial project-level variation remains unexplained, pointing to residual uncertainty conditional on type.

A common funding shock remains a concern: a firm that exhausts its capital may halt its entire pipeline, correlating project failures independently of founder ability. Columns (6) and (7) do not resolve this concern because private and never-public firms may be more exposed to such shocks. We therefore interpret the estimates as an upper bound on the ability channel. They establish an economically large, persistent firm-level component of project outcomes; the structural model separates entrepreneurial ability (firm-level component) from financing.

3.2 Liquidation risk during experimentation

Remaining private is costly because a firm may lose financing before its project is launched in the market. The model treats this event as independent of entrepreneurial ability, project quality, and market conditions. Although the data cannot verify independence, they reveal the frequency of such exits and the limited extent to which the firm's experimental news explains them.

Among the 377 liquidations in the firm-quarter panel, 44.3% involve firms whose lead drug had

Table 2: Firm-Level Persistence in Drug-Project Outcomes

This table reports leave-one-out regressions of drug-project outcomes on the outcomes of the same firm's other projects. The sample includes firm-drug pairs initiated by 2015 at firms with at least two such projects, giving each project at least five years of development records before the data end in 2020. The dependent variable equals one if the project was launched or registered. The independent variable is the leave-one-out success rate of the firm's sibling projects, defined as the firm's other projects and recomputed within each estimation sample. Initiation-year-quarter fixed effects correspond to the calendar quarter of the project's first recorded development status. ICD fixed effects include indicators for all second-level ICD-9 categories in which the drug is developed; a drug pursued in multiple categories enters each. Entry-stage fixed effects correspond to the project's development stage when it first enters the firm's pipeline. Column (5) computes the leave-one-out mean using only other projects initiated within five years of the focal project. Column (6) retains projects initiated before the firm's IPO, and column (7) retains firms that never went public during the sample period. Standard errors, clustered by firm, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	DV: Success						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sibling-project success rate	0.656***	0.637***	0.605***	0.279***	0.260***	0.263***	0.292***
	(0.023)	(0.024)	(0.023)	(0.021)	(0.020)	(0.021)	(0.023)
Initiation-year-quarter FE	No	Yes	Yes	Yes	Yes	Yes	Yes
ICD FE	No	No	Yes	Yes	Yes	Yes	Yes
Entry-stage FE	No	No	No	Yes	Yes	Yes	Yes
Sample	Full sample	Full sample	Full sample	Full sample	5-yr window	Private-era	Never public
Observations	22,545	22,545	22,545	22,545	22,189	20,176	17,086
Adjusted R^2	0.126	0.150	0.195	0.416	0.411	0.414	0.437

reached Phase I or beyond, and 22.3% involve firms in Phase II. Moreover, 69.5% had no recorded pipeline failure before liquidation, and only 21.2% had one during the preceding two years. These liquidations therefore often occur before the observed development history records a project failure.

Table 3 estimates a discrete-time hazard for private firm-quarters. The dependent variable equals one hundred in the liquidation quarter and zero otherwise, so coefficients are percentage-point changes in the quarterly exit probability. The regressors of interest indicate whether any drug in the firm's pipeline failed during the preceding four or eight quarters. We use pipeline-wide failures rather than lead-drug failures. Column (1) includes development-stage and year fixed effects, column (2) adds the lagged market valuation, and column (3) estimates the column (2) specification by logit, except for dropping year fixed effects.

Adverse project news has limited explanatory power for firm liquidation. A pipeline failure during the preceding four quarters raises the quarterly liquidation probability by 0.13 percentage points, significant only at the 10% level. The eight-quarter window and public-equity sentiment, proxied by the BTK price-to-sales ratio, add no explanatory power. The R^2 is 0.001 in both linear specifications. To a first approximation, liquidation timing is therefore only weakly related to information from the firm's experimentation.

This pattern motivates the model's liquidation risk. Development news is sparse, and firms often lose financing while their projects have neither failed nor advanced. The results establish the *magnitude* of a capital-supply risk only weakly related to observed project news, not its independence

Table 3: Liquidation of Private Biotech Firms

This table reports discrete-time hazard regressions of liquidation for the full firm-quarter panel of private biotech firms. In columns (1) and (2), the dependent variable equals one hundred in the quarter a firm liquidates or declares bankruptcy and zero otherwise. Column (3) is a logit using the untransformed indicator. A drug fails when it is classified as discontinued, suspended, or withdrawn, or when no development is recorded for sixteen consecutive quarters. Failure windows include every drug in the firm's pipeline. Quarters since last milestone advance is the number of quarters since the firm last moved a drug to a higher development stage. All specifications include development-stage fixed effects; columns (1) and (2) also include year fixed effects. Standard errors, clustered by firm, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	DV: Firm Liquidation		
	Linear probability		Logit
	(1)	(2)	(3)
Any drug failed in past 4 quarters	0.132*	0.131*	0.488*
	(0.068)	(0.068)	(0.265)
Any drug failed in past 8 quarters	0.027	0.025	0.107
	(0.052)	(0.052)	(0.240)
Quarters since last milestone advance	-0.003*	-0.003*	-0.015***
	(0.001)	(0.001)	(0.006)
Firm age in quarters	0.001	0.001	0.011**
	(0.001)	(0.001)	(0.005)
BTK P/S ratio (lagged)		-0.006	0.002
		(0.011)	(0.021)
Stage FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Observations	173,064	167,328	167,328
R^2	0.001	0.001	

from entrepreneurs' information, which remains a modeling assumption.

3.3 IPO timing and market conditions

The model also predicts that firms go public when sector valuations are high. The direct empirical counterpart is that a private firm's quarterly IPO probability increases with the biotech sector's valuation multiple. Panel A of Table 4 estimates a discrete-time hazard using the same firm-quarter panel as in Section 3.2. The dependent variable takes the value 100 in the IPO quarter and zero otherwise, and is regressed on the BTK price-to-sales ratio. Because the ratio varies by year-quarter, year fixed effects would absorb the variation of interest. Column (2) instead adds a linear trend, and column (3) adds entry-cohort fixed effects. Column (4) drops the stage fixed effects and instead includes an indicator for the lead drug being in Phase III or beyond. Column (5) estimates the column (2) specification by logit.

Relative to an unconditional quarterly listing probability of 0.366%, a one-unit increase in the BTK ratio raises the IPO probability by 0.052 to 0.054 percentage points across the preferred

Table 4: Market Conditions and the Decision to Go Public

This table reports discrete-time hazard regressions for the full firm-quarter panel of private biotech firms. In Panel A, the dependent variable equals one hundred in the IPO quarter and zero otherwise. Columns (1)–(4) are linear probability models; column (5) is a logit using the untransformed indicator. Panel B applies the column (2) specification to three outcomes: IPO, liquidation, and lead-drug failure. Column (3) of Panel A adds entry-cohort effects besides the lead-drug stage fixed effects. Standard errors, clustered by firm, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A: Market Conditions and the IPO Hazard

	DV: Firm IPO				
	Linear probability				Logit
	(1)	(2)	(3)	(4)	(5)
BTK P/S ratio	0.058***	0.054***	0.052***	0.053***	0.113***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.015)
Lead drug at Phase III or beyond				0.505***	
				(0.063)	
Firm age in quarters	-0.011***	-0.012***	-0.002	-0.010***	-0.047***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.003)
Linear time trend		0.011***	-0.029	0.007*	0.036***
		(0.003)	(0.038)	(0.003)	(0.008)
Stage FE	Yes	Yes	Yes	No	Yes
Entry-cohort FE	No	No	Yes	No	No
Observations	173,064	173,064	173,064	173,064	173,064
Adjusted R^2	0.004	0.004	0.005	0.002	

Panel B: Market Conditions and Other Hazards

DV:	*Firm IPO*	*Firm Liquidation*	*Lead Drug Failure*
	(1)	(2)	(3)
BTK P/S ratio	0.054***	-0.004	-0.003
	(0.009)	(0.004)	(0.009)
Firm age in quarters	-0.012***	-0.001**	0.012***
	(0.001)	(0.000)	(0.001)
Linear time trend	0.011***	0.013***	-0.003
	(0.003)	(0.002)	(0.003)
Stage FE	Yes	Yes	Yes
Observations	173,064	173,064	173,064
Adjusted R^2	0.004	0.000	0.001

linear specifications, or about 14% to 15% of the base rate. A one-standard-deviation increase of 2.17 units raises the listing probability by roughly one-third. The estimate is stable across all specifications. Development stage has an independent effect in the same direction: a lead drug at Phase III or beyond raises the quarterly listing probability by 0.505 percentage points. This pattern is consistent with milestone progress reducing information asymmetry, since later-stage

projects have generated more public evidence about project quality.

Panel B tests whether the sector valuation multiple also correlates with liquidation risk or development news. It applies Panel A's column (2) specification to three outcomes: IPO, liquidation, and lead-drug failure. The regressor that raises the listing hazard by 0.054 percentage points has essentially no effect on liquidation or failure, with estimates of -0.004 and -0.003 and standard errors small enough to rule out effects comparable to the listing estimate. Thus, public-market valuations affect IPO decisions without materially affecting liquidation or drug-failure rates. This finding motivates the assumption that market conditions are independent of liquidation shocks and project-development news.

3.4 IPO stage and post-IPO R&D performance

Finally, we provide suggestive evidence of adverse selection. Because entrepreneurial ability is privately observed, direct evidence is inherently difficult to obtain. A key prediction of our model, consistent with recent studies of dynamic adverse selection, is the *skimming property*: the timing of asset sales can signal seller quality. In our setting, IPO timing is reflected in the lead-drug development stage at IPO, so the downstream implication is that the stage at which a firm goes public should predict the performance of projects it initiates *after* the IPO. A post-IPO project is a fresh draw of project quality, distinct from the lead drug that brought the firm to market. Realized lead-drug quality therefore cannot mechanically link IPO stage to subsequent project performance. Entrepreneurial ability provides the persistent link between them. In the terminology of Section 2, the test asks whether the IPO-stage signal is about the jockey by examining the performance of "new" horses.

The sample contains all projects initiated after the IPO quarter by firms in the IPO sample, excluding the lead drug: 3,754 projects across 459 firms. The focal regressor indicates a late-stage IPO, defined as a lead drug at Phase III or beyond when the firm lists. The outcomes are whether the new project advances beyond its pipeline-entry stage (Panel A) and whether it ultimately receives FDA approval (Panel B). Both panels add controls cumulatively. Column (1) includes IPO-year and project-initiation-year fixed effects, column (2) adds ICD-9 category fixed effects, and column (3) adds firm characteristics at IPO. Column (4) applies the column (3) specification to projects observed for at least eight quarters after initiation.

Both outcomes point in the same direction. In column (3), a late-stage IPO is associated with a 7.2-percentage-point higher probability of subsequent project advancement and a 10.8-percentage-point higher probability of approval; both estimates are significant at the 1% level. Among projects observed for at least eight quarters, the respective estimates are similar at 8.3 and 11.8 percentage points.

These results indicate that IPO timing contains information about a persistent firm-level component to drug development, consistent with the model's entrepreneurial type. They do not rule out alternative explanations: firms that list later may be better capitalized, and financial resources are persistent. Controls for IPO valuation and pipeline size absorb some, but potentially not all,

Table 5: Lead-Drug Stage at IPO and the Outcomes of Subsequent Projects

This table relates the development stage of a firm's lead drug at IPO to the outcomes of projects initiated thereafter. The sample includes projects whose first recorded development status occurs strictly after the firm's IPO quarter, excluding the lead drug, for firms in the IPO sample defined in Section 2. Late-stage lead drug at IPO equals one if the lead drug had reached Phase III or beyond at the IPO date. The dependent variable equals one if the project advances beyond its pipeline-entry stage in Panel A and if it obtains approval in Panel B. ICD fixed effects include indicators for all second-level ICD-9 categories in which the drug is developed. Firm controls include the number of drug projects at IPO, log IPO valuation, and firm age at IPO. Column (4) applies the column (3) specification to projects observed for at least eight quarters after initiation. Standard errors, clustered by firm, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A: Project Advancement

	DV: Advancement			
	(1)	(2)	(3)	(4)
Late-stage IPO	0.060***	0.065***	0.072***	0.083***
	(0.022)	(0.021)	(0.023)	(0.026)
BTK P/S at IPO	0.006	0.008	0.008	0.010
	(0.007)	(0.006)	(0.006)	(0.006)
IPO-year FE	Yes	Yes	Yes	Yes
Initiation-year FE	Yes	Yes	Yes	Yes
ICD FE	No	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes
Observations	3,754	3,754	3,754	3,168
Adjusted R^2	0.045	0.130	0.131	0.133

Panel B: Project Approval

	DV: Approval			
	(1)	(2)	(3)	(4)
Late-stage IPO	0.127***	0.118***	0.108***	0.118***
	(0.030)	(0.027)	(0.030)	(0.033)
BTK P/S at IPO	-0.003	-0.002	-0.002	-0.001
	(0.008)	(0.007)	(0.007)	(0.008)
IPO-year FE	Yes	Yes	Yes	Yes
Initiation-year FE	Yes	Yes	Yes	Yes
ICD FE	No	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes
Observations	3,754	3,754	3,754	3,168
Adjusted R^2	0.079	0.154	0.155	0.130

of this variation. The data therefore exhibit the economically meaningful correlation predicted by the model, while remaining consistent with other persistent firm-level factors.

Together, these results establish the empirical content of the model's primitives: project outcomes have a persistent firm-level component distinct from project quality; project-failure news explains little of liquidation risk; public-market valuations predict listing but not liquidation or

drug-failure hazards; and the lead drug's stage at IPO predicts the quality of subsequently initiated projects. The evidence does not separate entrepreneurial ability from access to capital or information conveyed by IPO stage from resources associated with listing later. Nor can it quantify the distortion, because neither the option value of remaining private nor the cost of selling under asymmetric information is directly observed. The model developed next separately incorporates entrepreneurial type, financing risk, and public-market valuations to do so.

4 Model

4.1 Setup

Entrepreneurs and projects Time is discrete, $t = 0, 1, 2, \ldots$, and the horizon is infinite. All agents are risk neutral and discount future payoffs by the common factor $\beta < 1$. A single entrepreneur develops one drug project, which we interpret empirically as the firm's lead drug. At $t = 0$, she privately observes her type, $\theta \in \{h, l\}$, where h and l denote high and low ability, respectively. Investors do not observe θ, but know that it is drawn from a common prior,

$$q_0 = \Pr(\theta = h).$$

The type captures the entrepreneur's human capital: her ability to originate valuable ideas and to design and execute experiments that advance those ideas toward commercialization. It is fixed over time and privately known by the entrepreneur. Investors learn about it only from public histories generated by experimentation outcomes and equilibrium financing decisions.

Conditional on her type, the entrepreneur is endowed with a project whose latent quality is either good or bad. Let $x \in \{g, b\}$ denote this quality. The quality x is fixed at the outset but is not observed by any player, including the entrepreneur and investors. Thus, the entrepreneur's private information is about her type, not about the realized quality of the project.

As discussed in Section 2.1, ability and project quality are distinct. Ability is a durable characteristic that affects the likelihood that the entrepreneur originates or selects a promising scientific asset. Project quality is the latent biological potential of the particular molecule or compound under development. In the drug development setting, a high-ability entrepreneur may be better at choosing targets, selecting candidates, and designing informative trials, but ability does not mechanically determine biological success. We capture this by assuming that high-ability entrepreneurs draw good projects with higher probability:

$$p_0^h \equiv \Pr(x = g \mid \theta = h) > p_0^l \equiv \Pr(x = g \mid \theta = l).$$

Residual uncertainty about project quality remains even conditional on type and is resolved only through experimentation. The entrepreneur's private knowledge of θ therefore gives her a type-contingent prior over x. Investors begin with the prior q_0 over entrepreneur type and update their beliefs about both θ and x from public development histories.

To reach commercialization, the project must move through M ordered development stages, indexed by $m \in \{0, 1, \ldots, M\}$, with $m = 0$ denoting the initial stage. Reaching the final stage, $m = M$, corresponds to launch and generates terminal value $\alpha_t R$. The parameter $R > 0$ denotes the project's revenue scale, and α_t is a publicly observed valuation multiple whose dynamics are specified below. Together, $\alpha_t R$ is the market value of a launched project at date t. Before launch or termination, keeping the project active requires a per-period investment of γR, paid regardless of whether a development outcome is realized.

We refer to a transition from stage m to stage $m+1$ as passing a milestone, or as "progressing." The notation is generic, but its mapping to the data is direct: the state m indexes the lead drug's recorded development status. In the estimation, $m = 0$ represents discovery and preclinical development, $m = 1$ is Phase I, $m = 2$ is Phase II, $m = 3$ is Phase III, $m = 4$ is pre-registration, $m = 5$ is registration, and $m = 6$ is launch. Milestones are therefore the ordered public development status transitions observed in Cortellis, including clinical advances, regulatory reviews, and launch.

Learning about quality Project quality is learned through experimentation. Consider an active project at stage $m < M$. In each period, a development outcome is realized with probability $\eta_m \in (0, 1)$, where η_m captures the stage-specific arrival rate of public information. If no outcome is realized, the project remains at stage m and no learning about x occurs from the development process. Conditional on an outcome, the development technology has a bad-news structure. A good project passes with probability one and advances to stage $m + 1$. A bad project fails with probability $\lambda \in (0, 1)$, in which case failure is public, the project is terminated, and the payoff is zero. With probability $1 - \lambda$, a bad project passes and also advances to stage $m + 1$.

This technology implies that a failure perfectly reveals bad quality, whereas progressing is only partially informative. Let

$$p_m^\theta = \Pr(x = g \mid \theta, m)$$

denote the probability that a project developed by a type-θ entrepreneur is good after m milestones have been cleared, with initial value p_0^θ. Bayes' rule implies that, after the project progresses,

$$p_{m+1}^\theta = \frac{p_m^\theta}{p_m^\theta + \big(1 - p_m^\theta\big)(1 - \lambda)}, \qquad m = 0, \ldots, M - 1. \tag{1}$$

Because the updating operator in Equation (1) is strictly increasing in p_m^θ, the initial ordering $p_0^h > p_0^l$ implies $p_m^h > p_m^l$ for all m.

Investors do not observe θ. Given public belief $q = \Pr(\theta = h)$ at stage m, they assign probability

$$p_m(q) = \Pr(x = g \mid q, m) = q\, p_m^h + (1 - q)\, p_m^l. \tag{2}$$

This type-averaged probability summarizes investors' belief about project quality at that stage.

Financing and liquidity A project that remains under entrepreneurial ownership is exposed to liquidity risk. At the end of each period, with probability $\kappa \in (0,1)$, the entrepreneur or her current financiers cannot provide the capital required to continue development. This shock forces liquidation, terminates development, and yields zero. The shock captures idiosyncratic disruptions in the supply of private capital, rather than news about the project's fundamentals. In the biotech setting, such disruptions can reflect the entrepreneur's own liquidity constraints, limited follow-on reserves of existing venture investors, end-of-fund-life liquidation pressure, or constraints associated with limited-partner capital commitments. We assume the shock is independent of the entrepreneur's type, project quality, valuation state, and development outcomes, isolating residual capital-supply risk under entrepreneurial ownership.

The entrepreneur can eliminate this risk by financing the project through an IPO-like transaction with a competitive pool of deep-pocketed public investors. This interpretation matches the IPO event used in the structural estimation. For expositional convenience, we refer to this financing event as a sale of the project, since the entrepreneur transfers claims on the project's future cash flows to outside investors. After a sale, investors can finance continuation and are not subject to liquidity shocks. The sale decision therefore trades off eliminating liquidity risk against selling at a price based on investors' beliefs. Selling protects the project from forced liquidation, but selling before investors have fully learned the entrepreneur's type implies that the price may differ from the entrepreneur's type-contingent value based on her private information.

We abstract from the contracting problem within the sale transaction and summarize the transfer with a single price. If a sale occurs at public state (q, α, m), the entrepreneur receives

$$\Pi_I(q, \alpha, m),$$

where $\Pi_I(q, \alpha, m)$ is the investors' expected continuation value from owning the project at stage m when the entrepreneur is believed to be high type with probability q, net of future development costs. Thus, investors earn zero expected surplus from the transaction due to a fully competitive public equity market.

Valuation dynamics The payoff upon product launch depends on a time-varying valuation multiple. At the beginning of each period, all agents observe α_t. If the project reaches launch at date t, it generates terminal value $\alpha_t R$. Empirically, α_t corresponds to public-market valuation multiples for comparable biotech assets, namely, price-to-sales ratios in the biotech sector. These multiples vary over the development horizon and affect the value of commercializing, selling, or continuing the project.

We capture this variation with an exogenous AR(1) process,

$$\alpha_{t+1} = \bar{\alpha} + \rho \alpha_t + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \text{ i.i.d.}, \tag{3}$$

where $\rho \in (0,1)$. The unconditional mean of α_t is $\bar{\alpha}/(1-\rho)$. The innovations are independent of

the entrepreneur's type, project quality, and development outcomes.

The valuation state affects the entrepreneur's sale decision by changing the tradeoff between eliminating liquidity risk and selling at a price based on investors' beliefs. When α_t is high, the market value exposed to liquidation under entrepreneurial ownership is larger, which raises the benefit of financing. This force applies to both types. A low-type entrepreneur may sell to realize a high valuation, even at the cost of giving up mispricing opportunities due to investors' imperfect beliefs. A high-type entrepreneur may also sell while being underpriced, thereby avoiding the risk that a liquidity shock destroys a valuable project. Thus, although α_t is public and exogenous, it affects investor beliefs through equilibrium financing strategy.

Beliefs and timing Within each period, the timing is as follows. First, the valuation state α_t is realized and observed by all agents. Second, the entrepreneur chooses whether to sell the project; type θ sells with probability $s^\theta \in [0,1]$, where the dependence of s^θ on the public state (q, α_t, m) is suppressed. Third, if the entrepreneur does not sell, she pays the flow cost γR and continues. The liquidity shock and the development outcome are then realized.

Let q_t^- denote investors' belief at the start of period t that the entrepreneur is the high type. Observing the financing decision, if any, investors update their belief by Bayes' rule. Conditional on a sale, the relevant belief is

$$q^f = \frac{q_t^- \, s^h}{q_t^- \, s^h + (1 - q_t^-) \, s^l}, \tag{4}$$

which prices the transaction. Conditional on no sale, or waiting, the belief is

$$q^w = \frac{q_t^- \, (1 - s^h)}{q_t^- \, (1 - s^h) + (1 - q_t^-) \, (1 - s^l)}. \tag{5}$$

For an unsold project, if the project survives and no development outcome is realized, it remains at stage m with belief q^w. If a development outcome is realized and the project passes, it advances to stage $m+1$, and investors update their belief to

$$q_+^w = \frac{q^w \big(p_m^h + (1 - p_m^h)(1 - \lambda)\big)}{q^w \big(p_m^h + (1 - p_m^h)(1 - \lambda)\big) + (1 - q^w)\big(p_m^l + (1 - p_m^l)(1 - \lambda)\big)}. \tag{6}$$

This update reflects the informativeness of passing a milestone. Thus, for a continuing unsold project, the next-period prior q_{t+1}^- equals q_+^w after a passed milestone and q^w when no development outcome is realized. Figure 2 summarizes the timing.

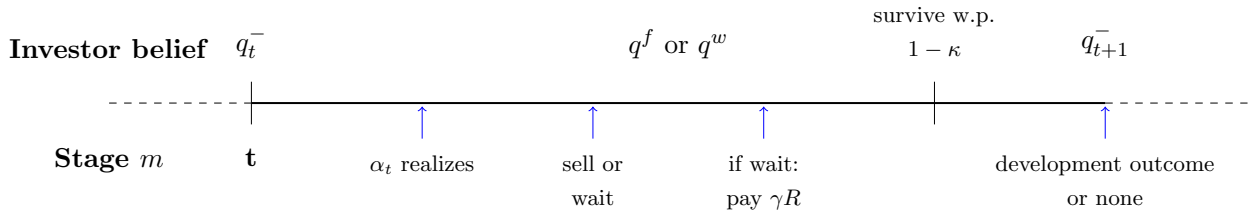
4.2 Equilibrium definition

We restrict attention to Markov Perfect Bayesian Equilibria (MPBE). The public state at the start of an active period is

$$z = (q^-, \alpha, m),$$

Figure 2: Timeline within a Period

The figure shows the sequence of events within a single period. The valuation state α_t is realized; the entrepreneur then chooses whether to sell the project or wait. If she waits, she pays the flow cost γR, survives the liquidity shock with probability $1-\kappa$, and may observe a development outcome. A development outcome updates the public belief from q_t^- to q_{t+1}^-.



where q^- is investors' belief that the entrepreneur is the high type, α is the valuation multiple, and m is the development stage. The entrepreneur privately observes her type $\theta \in \{h, l\}$ and follows a financing strategy

$$s^\theta(q^-, \alpha, m) \in [0, 1].$$

Given the other type's strategy, a type-θ entrepreneur's financing strategy is a best response that maximizes her continuation value. For $m < M$,

$$V^\theta(q_t^-, \alpha_t, m) = \max\big\{\, \Pi_I(q^f, \alpha_t, m),\ W^\theta(q_t^-, \alpha_t, m) \,\big\}, \tag{7}$$

where the first term is the payoff from selling and W^θ is the value of waiting. At launch, the terminal value is

$$V^\theta(q_t^-, \alpha_t, M) = \alpha_t R.$$

The wait value is

$$\begin{aligned} W^\theta(q_t^-, \alpha_t, m) \;=\; & (1-\kappa)\Big(\beta(1-\eta_m)\,\mathbb{E}\,V^\theta(q^w, \alpha_{t+1}, m) \\ & +\beta\eta_m\big(1-\lambda(1-p_m^\theta)\big)\,\mathbb{E}\,V^\theta(q_+^w, \alpha_{t+1}, m+1)\Big) - \gamma R. \end{aligned} \tag{8}$$

The wait value W^θ is the value of continuing under entrepreneurial ownership for one period. The entrepreneur pays the flow cost γR. With probability $1-\kappa$, the project survives the liquidity shock, otherwise it is liquidated and has zero continuation value. Conditional on survival, no development outcome arrives with probability $1-\eta_m$, leaving the project at stage m with belief q^w. A development outcome arrives with probability η_m. Given type θ, the project passes with probability $1-\lambda(1-p_m^\theta)$; conditional on passing, it advances to stage $m+1$ and investors update to q_+^w. Failure yields zero. The factor β discounts next-period continuation values, and the expectations integrate over α_{t+1} conditional on α_t.

The financing price Π_I is investors' zero-profit valuation. For any belief q, valuation state α_t, and stage $m < M$, this value is defined recursively by the same experimentation technology, but

without liquidity risk:

$$\begin{aligned}\Pi_I(q,\alpha_t,m) &= \beta(1-\eta_m)\,\mathbb{E}\,\Pi_I(q,\alpha_{t+1},m)\\ &\quad+\beta\eta_m\big(1-\lambda(1-p_m(q))\big)\,\mathbb{E}\,\Pi_I(q_+,\alpha_{t+1},m+1)-\gamma R,\end{aligned}\tag{9}$$

with terminal condition

$$\Pi_I(q,\alpha_t,M)=\alpha_t R.$$

Here q_+ is the posterior belief after a passed milestone, obtained from Equation (6) by replacing q^w with q. Because investors are not subject to liquidity shocks, Equation (9) omits the factor $(1-\kappa)$. This wedge is the source of gains from trade.

Formally, a Markov Perfect Bayesian Equilibrium consists of financing strategies $\{s^h, s^l\}$, a belief system, entrepreneur value functions $\{V^h, V^l\}$, and an investor pricing function Π_I such that the following conditions hold: (i) each type's financing strategy assigns positive probability only to actions that attain the maximum in Equation (7), given the other type's strategy and the belief system; (ii) beliefs are updated by Bayes' rule on the equilibrium path via Equation (4) to Equation (6); and (iii) the financing price satisfies the zero-profit condition (9). Signaling games of this kind typically admit multiple equilibria, sustained by different investor beliefs following unexpected financing decisions. When multiple MPBE satisfy these conditions, we select the high-type-preferred equilibrium. That is, among the equilibria of the continuation game at a given public state, we select the equilibrium that maximizes the high-type entrepreneur's value $V^h(q^-,\alpha,m)$.

At histories where financing occurs with zero probability under both types, Bayes' rule does not determine the posterior upon financing. We impose the off-path belief $q^f=0$, which is consistent with the D1 refinement (Cho and Kreps, 1987; Banks and Sobel, 1987). The D1 criterion restricts off-path beliefs toward the type for whom the deviation is relatively more attractive. In our setting, the high type's continuation value from waiting strictly exceeds that of the low type, due to $p_m^h > p_m^l$. Therefore, any off-path financing decision that is profitable for the high type is also profitable for the low type. An unexpected financing decision is consequently attributed to the low type.

We characterize the equilibrium in the next subsection. Before doing so, we establish several restrictions that narrow the set of financing strategies that can arise in equilibrium.

Lemma 1. *For any $q^- \in (0,1)$, there is no high-type-preferred MPBE in which, at some public state (q^-,α,m), the high type sells with interior probability, $0 < s^h(q^-,\alpha,m) < 1$, while the low type sells with positive probability, $s^l(q^-,\alpha,m) > 0$.*

Lemma 2. *For any $q^- \in (0,1)$, in any MPBE, if the high type sells with positive probability at some public state (q^-,α,m), then the low type also sells with positive probability. Moreover, if $s^h(q^-,\alpha,m)=1$, then $s^l(q^-,\alpha,m)=1$.*

Lemma 1 and Lemma 2 restrict the local strategy profiles that can arise in equilibrium. Lemma 2 rules out high-type-only financing. If only the high type financed, the financing posterior would assign probability one to the high type. The financing price would then reflect the high type's

project value, which strictly exceeds the low type's continuation value. The low type would therefore want to mimic. Hence, whenever the high type finances with positive probability, the low type must also finance with positive probability.

Lemma 1 further rules out interior mixing by the high type in the high-type-preferred equilibrium when the low type finances with positive probability. The reason is that high-type mixing can occur only at states where the high type is indifferent between financing and waiting. Among equilibria satisfying this indifference condition, increasing the high type's financing probability raises the posterior belief conditional on financing and improves the price received when financing occurs. The high-type-preferred selection therefore chooses the equilibrium with the largest feasible high-type financing probability. This eliminates interior high-type mixing.

Together, the two lemmas leave only three local configurations of the strategy pair (s^h, s^l): both types wait, $s^h = s^l = 0$; both types sell, $s^h = s^l = 1$; or the high type waits while the low type sells with positive probability, $s^h = 0$ and $s^l > 0$. The equilibrium characterization below shows that, along the valuation dimension, these regions are ordered by two cutoffs.

The model includes a revenue scale, R, that scales all cash flows. The next result shows that this scale parameter does not affect the entrepreneur's financing decision. It is therefore convenient to work with the normalized price and value,

$$\pi_I(q, \alpha, m) \equiv \frac{\Pi_I(q, \alpha, m)}{R}, \qquad v^\theta(q^-, \alpha, m) \equiv \frac{V^\theta(q^-, \alpha, m)}{R}.$$

Lemma 3. *The financing price Π_I and the entrepreneur's value function V^θ are homogeneous of degree one in the revenue scale R. Hence the normalized price π_I and value v^θ do not depend on R, and neither does the equilibrium financing strategy $s^\theta(q^-, \alpha, m)$. Moreover, the normalized price is affine in the valuation state:*

$$\pi_I(q, \alpha, m) = a_m(q)\,\bar{\alpha} + b_m(q)\,\rho^{M-m}\alpha - c_m(q), \tag{10}$$

where $a_m(q), b_m(q) > 0$ are strictly increasing in q and $c_m(q) \geq 0$. Closed-form expressions are in Appendix B.

The proof proceeds by backward induction. The terminal value αR, the flow cost γR, and the sale price are all linear in R. The entrepreneur's value function therefore inherits the same scaling, since it is the expected discounted value of these cash flows. The optimal financing strategy is independent of R because the financing decision is a comparison of two payoffs that are both proportional to R.

This homogeneity is important for the empirical estimation. The model can be applied to projects with different revenue scales because financing decisions depend on the normalized state (q^-, α, m) rather than on the dollar scale of the project. Projects targeting diseases with different market sizes, and hence different values of R, follow the same financing rule as a function of the valuation multiple α. This allows us to pool drugs across disease areas and estimate the model

using valuation multiples rather than dollar valuations. In particular, because R scales revenue, the sales-normalized valuation is the empirical counterpart of α, the state variable that enters the financing strategy.

4.3 Equilibrium characterization

By Lemmas 1 and 2, at any state (q^-, α, m) the strategy pair (s^h, s^l) must take one of three forms:

1. Pool to finance: $s^h = s^l = 1$;
2. Pool to wait: $s^h = s^l = 0$;
3. Separate to finance: $s^h = 0$ and $s^l > 0$.

We conjecture and verify an equilibrium in which these regions are characterized by valuation cutoffs. We first derive the cutoff conditions using the normalized payoffs from Lemma 3. Formally, for each state (q^-, α, m), the high type follows the cutoff strategy

$$s^h(q^-, \alpha, m) = \begin{cases} 1 & \text{if } \alpha \geq \alpha_h^\star(q^-, m), \\ 0 & \text{otherwise.} \end{cases}$$

When α is high, waiting exposes a more valuable project to liquidation risk. At a sufficiently high valuation multiple, this liquidation risk outweighs the pricing loss from selling under asymmetric information. The cutoff $\alpha_h^\star(q^-, m)$ is the value of α at which the high type is indifferent between selling and waiting.

At this cutoff, both types sell with certainty. The sale decision therefore provides no additional information, and the transaction is priced at the prior belief q^-, so the normalized sale price is $\pi_I(q^-, \alpha_h^\star, m)$. To evaluate the waiting payoff, we must specify the investors' belief. Since both types sell with certainty in this region, waiting is off the equilibrium path. Following the same D1 criterion used above, we assign the belief $q^w = 1$ to this deviation. The reason is that $p_m^h > p_m^l$ implies that the high type has a higher continuation value from waiting. Hence $\alpha_h^\star(q^-, m)$ solves

$$\begin{aligned} \pi_I(q^-, \alpha_h^\star, m) \;=\; & (1-\kappa)\Big(\beta(1-\eta_m)\,\mathbb{E}\, v^h(1, \alpha_{t+1}, m) \\ & +\beta\eta_m\big(1-\lambda(1-p_m^h)\big)\,\mathbb{E}\, v^h(1, \alpha_{t+1}, m+1)\Big) - \gamma. \end{aligned} \tag{11}$$

If investors' prior belief q^- is sufficiently low, however, the above equation may not have a solution because the financing price can remain too unfavorable. In that case, the high type never finances. We set $\alpha_h^\star(q^-, m) = +\infty$, and the pool-to-finance region is empty.

By Lemma 2, the low type sells wherever the high type sells. The low type may also sell in states where the high type waits. Her strategy is

$$s^l(q^-, \alpha, m) = \begin{cases} p(\alpha, q^-, m) & \text{if } \alpha \geq \min\{\alpha_l^\star(q^-, m), \alpha_h^\star(q^-, m)\}, \\ 0 & \text{otherwise,} \end{cases} \qquad p(\alpha, q^-, m) \in [0, 1].$$

To understand the above strategy, first consider the cutoff $\alpha_l^\star(q^-, m)$ that pins down the lower boundary of the separating to finance region. At this cutoff, the low type is indifferent between selling and waiting. In the separating region, the high type waits, so the financing decision reveals the low type and the sale posterior is $q^f = 0$. The normalized sale price is therefore $\pi_I(0, \alpha, m)$. Waiting, by contrast, is favorable news about type: because the high type waits with certainty while the low type sells with positive probability, the waiting posterior satisfies $q^w \geq q^-$. The lower bound $\alpha_l^\star(q^-, m)$ therefore captures the limiting case where the low type almost surely waits, and the market's belief remains at q^-. Thus $\alpha_l^\star(q^-, m)$ solves

$$\begin{aligned} \pi_I(0, \alpha_l^\star, m) &= (1-\kappa)\Big(\beta(1-\eta_m)\,\mathbb{E}\,v^l(q^-, \alpha_{t+1}, m) \\ &\quad +\beta\eta_m\big(1-\lambda(1-p_m^l)\big)\,\mathbb{E}\,v^l(q_+^-, \alpha_{t+1}, m+1)\Big) - \gamma, \end{aligned} \tag{12}$$

where q_+^- is the milestone update of q^- obtained from Equation (6) with $q^w = q^-$.

The relative location of the two cutoffs determines whether the separate-to-finance region is nonempty. If $\alpha_l^\star(q^-, m) \geq \alpha_h^\star(q^-, m)$, the separating region is empty: the low type sells only by pooling with the high type, and $s^l(q^-, \alpha, m) = 1$ whenever $\alpha \geq \alpha_h^\star(q^-, m)$. If $\alpha_l^\star(q^-, m) < \alpha_h^\star(q^-, m)$, then for $\alpha \in (\alpha_l^\star, \alpha_h^\star)$ the high type waits while the low type sells with positive probability. After observing no sale, investors update to

$$Q^\star(\alpha, q^-, m) = \frac{q^-}{q^- + (1-q^-)\big(1-p(\alpha, q^-, m)\big)} > q^-, \tag{13}$$

and $p(\alpha, q^-, m) \in (0, 1)$ is pinned down by the low type's indifference condition:

$$\begin{aligned} \pi_I(0, \alpha, m) &= (1-\kappa)\Big(\beta(1-\eta_m)\,\mathbb{E}\,v^l(Q^\star, \alpha_{t+1}, m) \\ &\quad +\beta\eta_m\big(1-\lambda(1-p_m^l)\big)\,\mathbb{E}\,v^l(Q_+^\star, \alpha_{t+1}, m+1)\Big) - \gamma, \end{aligned} \tag{14}$$

where $Q_+^\star$ is the milestone update of $Q^\star$. If the low type strictly prefers financing even under the most favorable waiting belief, the right-hand side of Equation (14) evaluated at $Q^\star = 1$ lies below the price, and the equilibrium has $p(\alpha, q^-, m) = 1$.

Together, the two cutoffs partition the valuation line into at most three regions, with the convention that $\alpha_h^\star(q^-, m) = +\infty$ when the high type never finances. For $\alpha < \min\{\alpha_l^\star, \alpha_h^\star\}$, both types wait. If $\alpha_l^\star < \alpha_h^\star$, then for $\alpha \in (\alpha_l^\star, \alpha_h^\star)$ the high type waits while the low type finances with positive probability. If $\alpha_h^\star < +\infty$, then for $\alpha \geq \alpha_h^\star$, both types finance.

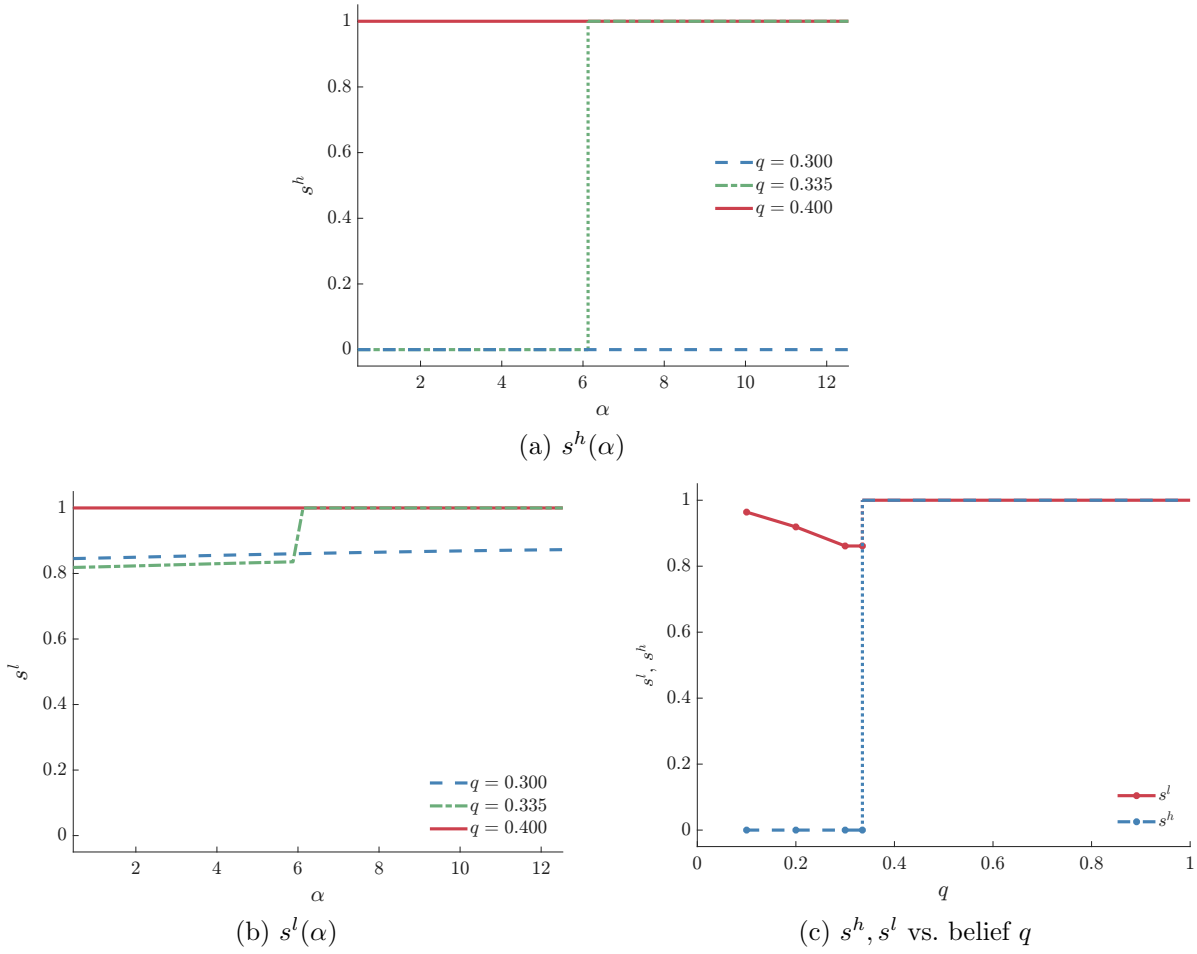
Proposition 1. *There exists $\bar{\kappa} \in (0, 1)$, defined in Appendix B, such that if $\kappa \geq \bar{\kappa}$, then the financing strategies in the high-type-preferred MPBE follow the cutoff strategy constructed above. For each belief-stage pair (q^-, m) with $m < M$, there exists a unique pair of cutoffs*

$$\big(\alpha_l^\star(q^-, m), \alpha_h^\star(q^-, m)\big) \in \mathbb{R} \times \big(\mathbb{R} \cup \{+\infty\}\big),$$

where the low-type cutoff $\alpha_l^\star(q^-, m)$ solves Equation (12), and there is a threshold $\tilde{q}(m)$ such that the high-type cutoff $\alpha_h^\star(q^-, m)$ solves Equation (11) if $q^- > \tilde{q}(m)$ and satisfies $\alpha_h^\star(q^-, m) = +\infty$ otherwise.

Figure 3: Illustration of the Equilibrium Cutoff Strategy

The figure illustrates the equilibrium financing strategies at the estimated parameters. Panels (a) and (b) plot the high- and low-type selling probabilities, s^h and s^l, against the valuation state α at development stage $m = 5$ for three levels of the public belief q. Panel (c) plots both probabilities against the belief q at the median valuation state.



(a) $s^h(\alpha)$

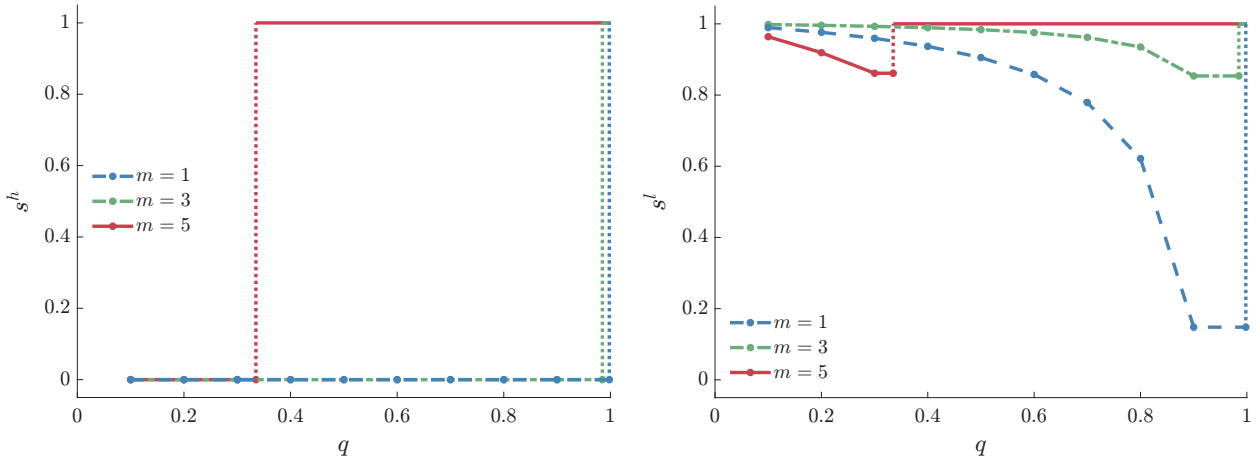
(b) $s^l(\alpha)$

(c) s^h, s^l vs. belief q

Figure 3 illustrates the equilibrium financing strategies at the estimated parameters. Panel (a) plots the high-type financing probability as a function of the valuation multiple α for three values of the belief q^-, holding the stage fixed. The high type follows a cutoff rule: financing occurs with probability zero below $\alpha_h^\star(q^-, m)$ and with probability one above it. The cutoff is decreasing in q^-. When investors are more optimistic about the entrepreneur's type, the pricing loss from financing under asymmetric information is smaller, so the high type is willing to finance at a lower valuation multiple. The blue dashed line corresponds to the case $q^- \leq \tilde{q}(m)$, in which $\alpha_h^\star(q^-, m) = +\infty$ and the high type never finances. By contrast, when the belief is sufficiently optimistic, the high type finances at a much lower cutoff near zero.

Figure 4: Equilibrium Strategies across Development Stages

The figure plots the equilibrium selling probabilities against the public belief q at the estimated parameters, for development stages $m = 1, 3, 5$. Panel (a) shows the high type, s^h, and Panel (b) the low type, s^l.



(a) s^h vs. belief q

(b) s^l vs. belief q

Panel (b) plots the low-type financing probability as a function of α for the same beliefs and parameters. The figure highlights two forces. First, the low type mimics the high type in the pool-to-finance region: for $\alpha \geq \alpha_h^\star(q^-, m)$, both types finance with certainty. Second, when the high type waits, the low type may still finance with positive probability. This occurs in the separate-to-finance region, $\alpha \in (\alpha_l^\star(q^-, m), \alpha_h^\star(q^-, m))$, where the low type mixes to remain indifferent between financing and waiting. Within this region, the low-type financing probability changes only modestly with α, reflecting two offsetting forces. A higher α increases the value at stake in liquidation, which makes current financing more attractive. At the same time, a higher α also raises the value of waiting, because the valuation process is more likely to reach the pooling region in a future period, allowing the low type to benefit from overpricing when both types finance.

Panel (c) instead plots the financing strategies as functions of the belief q^-, holding the price-to-sales ratio α fixed at the median. The high-type strategy has a bang-bang structure: as q^- crosses a threshold, the high type switches from waiting to financing with certainty. A higher q^- places more weight on the high type's project prospects in the financing price, reducing the high type's pricing loss and making financing more attractive. The low-type financing probability instead strictly decreases in the separate-to-finance region. The reason is dynamic. In this region, no financing is favorable news about type because the high type waits while the low type finances with positive probability. A higher prior belief makes the posterior after no financing more likely to move the project into the pool-to-finance region in the next period. This raises the low type's value of waiting. In equilibrium, the low type lowers her current financing probability. This makes no financing less favorable news about type, weakens the belief update from waiting, and offsets the stronger waiting incentive, leaving the low type indifferent between financing and waiting.

Figure 4 illustrates how equilibrium financing strategies vary across development stages. Panel

(a) plots the high-type financing probability as a function of the belief q^- for three stages m, holding the valuation multiple α fixed. Each line exhibits the bang-bang structure described above: as q^- crosses a stage-specific threshold, the high type switches from waiting to financing with certainty.

The financing region expands as the project advances. At early stages, the high type rarely finances because asymmetric information is severe and the pricing loss is large. Later-stage projects have cleared more milestones. As the project advances, Bayesian updating makes investors more optimistic that the underlying project quality is good. Put differently, the gap between p_m^h and p_m^l narrows as they both approach one. This mitigates the information asymmetry problem because distinguishing entrepreneur types is less essential to investors. The high type therefore exercises the financing option at a lower belief threshold in later stages. In contrast, the low type finances with positive probability even at early stages, as shown in Panel (b).

The high type's tendency to wait at early stages is fundamental to the model's tradeoff. She delays financing to avoid the pricing loss from asymmetric information, hoping that subsequent milestone outcomes improve public beliefs about project quality and, indirectly, about her type. Delaying, however, exposes the project to liquidity risk. In equilibrium, the high type therefore faces two sources of value loss: underpricing when she finances, and liquidation risk when she waits. Section 6 quantifies these losses.

5 Structural Estimation

The equilibrium characterization in Section 4.3 implies that high-ability entrepreneurs may delay financing to avoid being pooled with low-ability entrepreneurs, at the cost of continued exposure to liquidation risk. The magnitude of this trade-off is a quantitative question. We therefore bring the model to the biotech panel described in Section 2, calibrating a small set of parameters and estimating the remaining key parameters by SMM (McFadden, 1989; Pakes and Pollard, 1989). Online Appendix A.2 through Online Appendix A.4 describe the numerical solution, simulation procedure, and optimization routine.

5.1 Parameters and calibration

We estimate six primary parameters with direct economic interpretations. Together, they govern four forces in the model: the severity of asymmetric information, the speed at which public experimentation resolves it, the liquidation risk faced by private firms, and the cost of experimentation.

The severity of asymmetric information is governed by the pair (δ, p_0^l), where $\delta \equiv p_0^h - p_0^l$. The entrepreneur privately observes her type, and this private information matters because type shifts the prior probability that her project is good. If $\delta = 0$, the two types would draw projects from the same quality distribution, the financing decision would convey no information about project quality, and the model would collapse to its symmetric-information benchmark. The gap δ should not be interpreted only in absolute terms. Its economic importance depends on p_0^l, the low type's project-quality prior. A given gap implies more severe adverse selection when low-type projects are

unlikely to be good, but a weaker friction when even low-type entrepreneurs tend to draw successful projects.

The speed of learning is governed by (q_0, λ). The prior q_0 determines investors' initial belief that the entrepreneur is high type. The parameter λ, the probability that a bad project fails conditional on a development outcome, determines the informativeness of a passed milestone. When λ is near one, passing a milestone is strong evidence of project quality, so both project uncertainty and asymmetric information are resolved quickly. When λ is near zero, experimentation reveals little, leaving both scientific uncertainty about the project and asymmetric information about entrepreneur type unresolved even after repeated milestones.

The remaining two parameters govern the cost of delaying financing. The liquidity-shock probability κ determines the probability that a privately held project is liquidated for reasons unrelated to a development outcome. The flow cost γ is the quarterly investment required to keep a program active, expressed per dollar of the project's expected revenue. It determines the direct cost of continued experimentation and therefore the feasibility of remaining private while awaiting additional information. Collecting the six parameters in

$$\theta = (\delta,\ p_0^l,\ q_0,\ \lambda,\ \kappa,\ \gamma), \qquad \delta \equiv p_0^h - p_0^l \geq 0,$$

we parameterize the type ordering by the ability gap rather than by p_0^h directly, so that $p_0^h \geq p_0^l$ holds by construction. Because none of these parameters is directly observable, we estimate them jointly from the financing and development histories in the data.

We set $M = 6$, so that the model's development path maps to the seven ordered development states used in the estimation: discovery and preclinical development, Phase I, Phase II, Phase III, pre-registration, registration, and launch. Accordingly, $m = 0$ represents discovery and preclinical development, while $m = M$ represents a launched drug. This mapping aligns the model with the institutional sequence of drug development.

The remaining ten parameters are calibrated outside the estimation: the discount factor β, the three parameters $(\bar{\alpha}, \rho, \sigma)$ governing the valuation multiple, and the six stage-specific arrival rates $\eta_0, \ldots, \eta_5$. These parameters are disciplined by evidence independent of financing decisions, including Treasury yields, the time series of public-market valuation multiples in the biotech sector, and transition times observed for the broader population of U.S. drug candidates. Table 6 reports the calibrated values.

Discount factor We set the quarterly discount factor β using the historical mean annualized yield on ten-year U.S. Treasury securities from 1960 through 2023. The mean annual yield over this period is 5.82%, which implies a quarterly discount factor of $\beta = (1.0582)^{-1/4} = 0.9860$.

Valuation multiple We estimate the AR(1) process in Equation (3) using the quarterly price-to-sales ratio of the NYSE Arca Biotechnology Index over 1993Q2 to 2023Q2, a sample of 121 quarters. The estimated persistence is $\rho = 0.880$ and the innovation standard deviation is $\sigma = 1.313$. The

implied unconditional mean is 6.49, so the drift is $\bar{\alpha} = (1-\rho) \times 6.49 = 0.777$. The process is highly persistent, with a half-life of roughly five and a half quarters. This persistence makes financing timing economically consequential, because unfavorable valuation states are expected to persist for multiple quarters.

Outcome arrival rates The rates η_m govern how often a drug candidate at stage m generates public news about its development outcome. Because η_m is a feature of the experimentation technology rather than of the entrepreneur, we calibrate it from the full Cortellis universe of U.S. drug development records. For each stage, we compute the average number of quarters a candidate remains in that stage before it either advances or is recorded as failed, and set η_m equal to the inverse of that duration. The resulting arrival rates imply average times spent in each stage of roughly ten quarters in discovery or preclinical development, thirteen to fifteen quarters in each of the three clinical phases, eight quarters in pre-registration, and twelve quarters in registration. These long durations imply that public development outcomes arrive infrequently, which is why investor learning about project quality and entrepreneur ability is gradual.

Revenue scale The project's revenue scale R requires no calibration. By Lemma 3, both the financing decision and the normalized price π_I are invariant to R, so the model applies to firms with different market potential as long as valuations are expressed per dollar of projected sales. This normalization corresponds to the IPO valuation measure defined in Section 2: market capitalization in the IPO quarter divided by the lead drug's projected average annual sales if successfully launched. The revenue scale therefore enters the empirical work only through this normalization, and the estimated flow cost γ is correspondingly interpreted as a development cost per dollar of projected annual sales.

5.2 Estimation

We estimate θ by SMM. For each candidate θ, we solve the equilibrium of Section 4.3 numerically on a discretized state space, simulate firm histories, and compare the resulting vector of simulated moments $m^s(\theta)$ with its empirical counterpart m^d. The estimator solves

$$\hat{\theta} = \arg\min_{\theta} \left(m^s(\theta) - m^d\right)' W \left(m^s(\theta) - m^d\right), \tag{15}$$

where W is the inverse of the estimated covariance matrix of the empirical moments. We construct this covariance matrix from firm-level influence functions (Erickson and Whited, 2002). This approach accommodates the different populations on which the moments are defined: several moments are computed among firms that go public, one is computed over the full firm cross-section, and three are computed as rates over the firm-quarter panel. Clustering the influence functions at the firm level allows the weights to reflect both differences in precision across moments and correlations among them.

Table 6: Calibrated Parameters

This table reports the parameters calibrated outside the structural estimation. The discount factor is the quarterly equivalent of the 1960–2023 average annual yield on ten-year U.S. Treasury securities. The parameters of the valuation process are estimated from an AR(1) fitted to the quarterly price-to-sales ratio of the NYSE Arca Biotechnology Index over 1993Q2 to 2023Q2. The arrival rates η_m are the inverse of the mean number of quarters a drug candidate spends at development stage m before advancing or failing, computed from the Cortellis universe of U.S. drug development records.

Parameter	Symbol	Value
Panel A: Preferences and valuation process		
Quarterly discount factor	β	0.9860
Persistence of valuation multiple	ρ	0.8804
Innovation standard deviation	σ	1.3127
Drift of valuation multiple	$\bar{\alpha}$	0.7770
Panel B: Experimentation technology		
Outcome arrival rate, Discovery / preclinical	η_0	0.0947
Outcome arrival rate, Phase I	η_1	0.0744
Outcome arrival rate, Phase II	η_2	0.0676
Outcome arrival rate, Phase III	η_3	0.0712
Outcome arrival rate, Pre-registration	η_4	0.1272
Outcome arrival rate, Registration	η_5	0.0834

We simulate the model along the observed panel rather than in an artificial economy. Firms differ along dimensions that the model takes as given: the stage at which the lead drug first appears, the calendar quarter of entry and thus the segment of the biotech valuation cycle to which the firm is exposed, and the number of quarters observed before the panel ends in 2020Q4. Each firm enters the simulation in the quarter and at the development stage at which its lead drug first appears in the data. It then faces the empirically observed sequence of biotech valuation multiples $\{\alpha_t\}$ over its observed horizon. We draw the entrepreneur's type from the prior q_0. Conditional on type and entry stage, we draw the lead drug's latent quality using the type-contingent posterior implied by the milestones already cleared before the drug first appears in the data. In each subsequent quarter, we draw whether a development outcome arrives, whether a bad project fails, whether a liquidity shock occurs, and whether the entrepreneur finances at the equilibrium probability implied by the current public state. A simulated history ends when the firm first finances, fails, or is liquidated, or is right-censored at the end of its observed panel, whichever comes first. Because entry dates, entry stages, and the aggregate state come directly from the data, the simulated and observed panels have the same entry composition, exposure to market conditions, and right-censoring. The moments therefore require no separate truncation adjustment, and differences in outcomes reflect the model's decision rules rather than differences in the environment.

We target eight moments, listed in the first column of Table 7. Four moments are defined among IPO firms: the mean scaled IPO valuation, the variance and skewness of the lead-drug stage at IPO, and the share of IPOs occurring at Phase III or later. One moment is defined over the full firm cross-section: the share of firms whose lead drug ever reaches Phase II. The remaining three

Table 7: Targeted Moments: Model and Data

This table compares the eight targeted moments generated by the model at the parameter estimates reported in Table 8 with their empirical counterparts. The IPO valuation multiple is market capitalization in the IPO quarter divided by the lead drug's projected average annual sales if successfully launched and is winsorized at the 1st and 99th percentiles. The stage at IPO ranges from 0 (discovery and preclinical) to 6 (launched). The bankruptcy and lead-drug failure hazards are quarterly rates. Each is calculated as the number of relevant events divided by the total number of at-risk firm-quarters. A bankruptcy event occurs when a firm is liquidated. A lead-drug failure event occurs when the drug is discontinued, suspended, withdrawn, or no development reported for at least sixteen quarters. Both events are counted only if they occur after the firm's entry quarter and before the firm goes public. The progression rate is the mean of the quarterly indicator for a lead-drug stage advance across all firm-quarters.

Moment	Model	Data
Mean IPO valuation multiple	1.4548	1.4919
Variance of lead-drug stage at IPO	1.8756	2.0031
Skewness of lead-drug stage at IPO	0.8289	0.8515
Quarterly bankruptcy hazard (%)	0.236	0.224
Quarterly lead-drug failure hazard (%)	1.007	0.992
Share of IPOs at Phase III or later (%)	21.50	23.14
Share of firms ever reaching Phase II (%)	33.95	36.65
Quarterly lead-drug progression rate (%)	1.678	1.655

moments are quarterly rate moments among firms that have not yet gone public: the liquidation hazard, the lead-drug failure hazard, and the probability that the lead drug progresses to a higher stage. With eight moments and six parameters, the model is overidentified.

The criterion in Equation (15) is not globally smooth because the equilibrium features cutoffs on a discretized grid and collapses to a corner in some regions of the parameter space. We search for the global minimum using the three-step TikTak algorithm (Arnoud et al., 2019): a multistart local search from 10,000 quasi-random points, a second round of search based on the convex combination of the 100 most promising basins, and a final high-precision refinement of the best solution. We reject any candidate parameter vector for which the financing price, evaluated at a public belief of zero, is negative over the entire valuation grid at any development stage. Online Appendix A.4 provides further details.

5.3 Identification

We estimate all six parameters jointly. Though each moment responds to every parameter to some extent, we first describe the primary economic channels through which the data identify each primitive.

Identification begins with the asymmetry between the two types' equilibrium strategies. By Proposition 1, the high type follows a bang-bang rule: at a given stage and market valuation multiple, she waits until the public belief crosses a threshold and then finances with probability one. The low type instead mixes from the first stage, financing with an interior probability that keeps her indifferent. These different equilibrium strategies have different implications for the

cross-section of financing decisions. High-type IPOs concentrate at later stages, with a thin left tail generated by rare cases in which prolonged waiting without financing is itself interpreted as favorable news about type. Low-type IPOs begin at stage zero and produce a right tail composed of entrepreneurs whose projects repeatedly progress by chance and ultimately finance alongside high types. Consequently, the *distribution of the development stage at which firms go public*, especially its dispersion and asymmetry, is central to identifying the informational environment.

The cost of experimentation, γ By Lemma 3, the normalized financing price is affine in the valuation multiple. The flow cost enters only through the intercept $c_m(q)$ in Equation (10), which is proportional to γ. Holding the calibrated valuation process and arrival rates fixed, γ is the only parameter that shifts the level of the financing price without changing the informativeness of a milestone. The average valuation multiple at IPO, defined as market capitalization per dollar of the lead drug's projected annual sales, is therefore informative about γ. A higher flow cost reduces the valuation at IPO, holding fixed the information revealed to the market.

The informativeness of milestones, λ Through the updating rules in Equation (1) and Equation (6), λ governs how strongly beliefs respond when a project progresses. When λ is large, a passed milestone conveys strong information about project quality, public beliefs update sharply, and the high type's financing threshold is reached after relatively few successful milestones. IPOs therefore cluster within a narrower range of development stages. When λ is small, learning is slow, the high type waits longer for public beliefs to improve, and IPOs are more dispersed along the development path. The variance of the stage at IPO is therefore informative about λ.

The low type's project prior, p_0^l Because the low type mixes from stage zero, she accounts for the mass of very early listings, while low types whose projects repeatedly progress by chance form the right tail of the stage distribution. Raising p_0^l increases her continuation value from waiting, reduces her early mixing probability, lowers the mass at stage zero, and lengthens the right tail. The skewness of the stage distribution moves monotonically with p_0^l, whereas its variance is comparatively insensitive. The two stage moments therefore help distinguish p_0^l from λ: skewness captures the location of the mass of early listings, while variance captures dispersion along the development path.

The prior on entrepreneur ability, q_0 Conditional on the arrival of a development outcome, a good project always progresses, whereas a bad project fails with probability λ. Because a high type's project is good with probability p_0^h, compared with p_0^l for a low type, a higher q_0 increases the share of projects that survive successive milestones. The fraction of firms whose lead drug clears two milestones and reaches Phase II is therefore informative about the initial type composition. This progression moment helps identify q_0, whereas financing decisions respond to q_0 only through equilibrium beliefs.

Liquidity risk, κ The liquidity shock is exogenous and independent of type, stage, project quality, and market conditions. We map this shock to observed bankruptcy and liquidation events among private firms. The quarterly bankruptcy or liquidation rate is therefore directly informative about κ.

The ability gap, δ The ability gap affects the pre-IPO failure hazard through the composition of project quality, not through the experimentation technology. Conditional on the arrival of a development outcome, a bad project fails with probability λ regardless of the entrepreneur's type. The parameter δ instead changes the fraction of projects under development that are bad. A type-θ entrepreneur's project is bad with probability $1 - p_m^\theta$, so the failure hazard among private firms at stage m is proportional to

$$\eta_m \lambda \big[\omega_m \big(1 - p_m^h\big) + (1 - \omega_m)\big(1 - p_m^l\big) \big],$$

where ω_m is the share of high types among private firms at that stage. This expression shows the direct composition effect. Holding ω_m and p_0^l fixed, a larger δ raises p_m^h and reduces the share of bad projects among high-type entrepreneurs. This lowers the pre-IPO failure hazard. Equilibrium financing behavior reinforces this effect by changing the composition of firms that remain private. A wider ability gap makes pooling more costly for the high type, so she waits longer. Both responses increase the representation of high-type entrepreneurs among private firms. Since high-type entrepreneurs are less likely to hold bad projects, this indirect composition channel further reduces the pre-IPO failure hazard. The failure hazard is therefore informative about δ conditional on q_0 and p_0^l.

The two remaining targeted moments, the share of IPOs occurring at Phase III or later and the average quarterly probability of lead-drug progression, are not assigned to a single parameter. Together, they discipline the right tail of the financing decision and the overall pace of experimentation, providing the model's overidentifying restrictions.

Local sensitivity To assess how the moments identify the parameters, we compute the sensitivity matrix of parameter estimates to moments following Andrews et al. (2017),

$$\Lambda = \big(G'WG\big)^{-1} G'W, \qquad G = \left.\frac{\partial m^s(\theta)}{\partial \theta'}\right|_{\theta=\hat{\theta}},$$

which gives the derivative of the estimate with respect to the empirical moments. Specifically, Λ_{kj} is the change in $\hat{\theta}_k$ induced by a one-unit change in moment j. Because the eight moments have different units, we report the corresponding elasticities $\Lambda_{kj}\hat{m}_j/\hat{\theta}_k$, which measure the percentage change in the estimate induced by a one-percent change in the moment.

Computing G requires some discussion because the simulated moments are step functions of θ. The equilibrium cutoffs lie on discrete belief grids, so a perturbation that is too small to move a cutoff leaves the moments unchanged and can produce a two-point difference of exactly zero. We

Table 8: Structural Parameter Estimates

This table reports the SMM estimates of the structural parameters. The estimates minimize the criterion in Equation (15). We simulate the model along the observed firm-quarter panel described in Section 2, taking each firm's entry date, entry stage, and realized path of the biotech valuation multiple directly from the data. We estimate the ability gap $\delta = p_0^h - p_0^l$ directly. The implied high-type project prior p_0^h is reported in italics, and its standard error is calculated using the delta method. Standard errors are reported in parentheses.

Parameter	Symbol	Estimate	Std. error
Ability gap in project prior	$\delta = p_0^h - p_0^l$	0.6716	(0.0432)
Low type's project prior	p_0^l	0.1187	(0.0196)
Implied high type's project prior	p_0^h	*0.7903*	*(0.0424)*
Prior probability of high ability	q_0	0.4571	(0.0212)
Probability a bad project fails a trial	λ	0.8517	(0.0541)
Quarterly liquidity-shock probability	κ	0.0023	(0.0003)
Quarterly development cost (per unit of R)	γ	0.0139	(0.0018)

address this issue by estimating each derivative as the slope from a local linear regression of the simulated moment on the parameter over a symmetric window, a standard approach to smoothing noisy simulation output (Hong et al., 2015). We fit each slope over a window of $\pm 2.5\%$ around the estimate, which contains 25 perturbations. Online Appendix A.4 describes the procedure and the choice of window.

Online Appendix A.5 reports the results. Two findings are worth noting. First, the Jacobian matrix confirms that the targeted moments respond to their designated parameters through the economic mechanisms described above. Second, the sensitivity matrix shows that identification is distributed across the full set of moments rather than driven by any single one. A one-percent perturbation to any targeted moment changes any parameter estimate by at most about four percent, indicating that the estimates are not unduly sensitive to modest perturbations of individual moments (Andrews et al., 2017). In particular, the ability gap and the low-type prior are separately identified, so both the high-type prior $p_0^h = \delta + p_0^l$ and its decomposition are disciplined by the targeted moments.

5.4 Estimates and model fit

Table 8 reports the SMM estimates. Four features stand out.

First, the estimated ability gap is large. The project-quality priors are $p_0^l = 0.119$ and $p_0^h = 0.790$, implying that a project originated by a high-ability entrepreneur is nearly seven times as likely to be fundamentally good as one originated by a low-ability entrepreneur. Together with the initial prior $q_0 = 0.457$ that an entrepreneur has high ability, these estimates imply that approximately 43% of newly initiated programs are viable. The majority are therefore not viable in latent quality. In equilibrium, even viable high-type projects may fail to reach the market because high types delay financing and become disproportionally more exposed to liquidation risk. Together, these forces are consistent with the well-documented fact that most drug candidates never reach the market

(Wong et al., 2019). The estimates imply that project viability is low on average but varies sharply with entrepreneur type. Because the entrepreneur privately observes the type that generates this dispersion, private financing decisions are subject to severe adverse selection.

Second, experimentation is highly informative and quickly narrows the informational gap. At $\lambda = 0.852$, a bad project fails with probability about six out of seven conditional on a development outcome. Passing a milestone is therefore strong, although not conclusive, evidence of quality. Applying the updating rule in Equation (1), one passed milestone raises the project-quality posterior from 0.119 to 0.476 for a low-ability entrepreneur and from 0.790 to 0.962 for a high-ability entrepreneur. The ratio of these posteriors falls from 6.7 to 2.0 after one passed milestone and to 1.2 after two. These estimates explain why early financing is costly for a high type: a small number of additional milestones would substantially reduce the informational gap, and financing before those milestones are observed forgoes that information, echoing the pattern in Figure 4.

Third, liquidity risk is modest in any given period but accumulates over the long development process. The estimated hazard is $\kappa = 0.0023$ per quarter, or approximately 0.9% per year. Conditional on remaining private for ten years, a firm faces nearly a 9% probability of forced liquidation. This wedge generates gains from trade in the model. It also makes waiting costly, especially for high-type entrepreneurs, who delay financing in equilibrium to avoid being pooled with low types.

Fourth, the flow cost of experimentation is economically significant relative to the asset under development. The estimate $\gamma = 0.0139$ implies that keeping a program active costs 1.39% of the lead drug's projected annual sales per quarter, or approximately 5.6% per year.

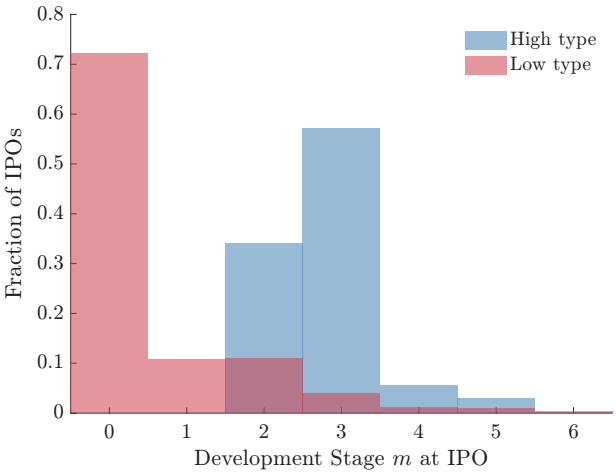
The second and third columns of Table 7 report the model fit. Overall, the model matches the targeted moments well. The model-implied IPO valuation ratio is 1.45, close to 1.49 in the data. It also produces a stage-distribution skewness of 0.83, a quarterly lead-drug failure hazard of 1.01%, and a quarterly lead-drug progression rate of 1.68%. The corresponding data moments are 0.85, 0.99%, and 1.65%. The model further captures the bankruptcy hazard and key features of firms' development stages at IPO and subsequent drug progression. Thus, despite its parsimonious structure, the model jointly accounts for the level of valuations, the distribution of development stages, and the pace of experimentation in the data. This joint fit is particularly important because these are the key margins underlying the counterfactuals in Section 6.

Before turning to the counterfactuals, we use the estimated model to illustrate its equilibrium mechanisms. Because entrepreneur type and project quality are observed in the simulated histories, we can characterize how latent types sort into IPOs, market windows, and failure histories. Note that these exercises are model-implied decompositions of the simulated economy rather than additional empirical moments or estimates of individual firms' types.

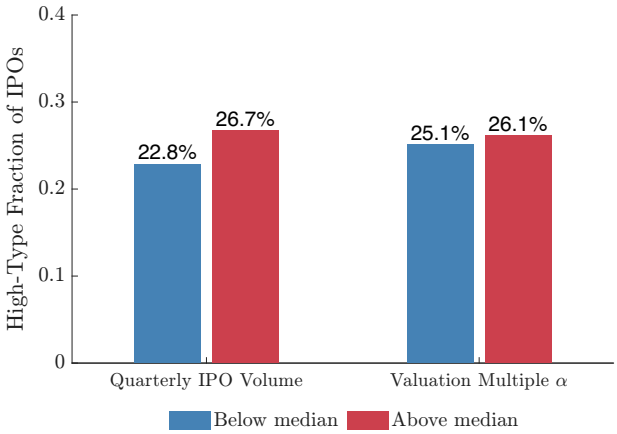
Figure 5 shows the model-implied composition of IPOs by entrepreneur type. Panel (a) plots the distribution of IPO stages separately for simulated high- and low-type entrepreneurs. The two types concentrate at different points in the development process. Low types are concentrated at early stages, while high types are concentrated at later stages. This pattern reflects the central signaling force in the model: high types delay financing to avoid being pooled with low types, while

Figure 5: Type Sorting into IPOs

Figure 5 shows how simulated high- and low-type entrepreneurs finance through IPOs in the estimated model. Each entrepreneur is randomly assigned a type according to the estimated type distribution. Conditional on this type and the firm's entry stage, project quality is drawn from the type-contingent posterior implied by the milestones already cleared. Type and project quality then determine the firm's development and financing history through the model's equilibrium strategy. Panel (a) plots the distribution of the lead-drug stage at IPO for high- and low-type entrepreneurs. In Panel (b), we record the calendar quarter of each IPO and classify it as being below or above the median quarterly IPO count in the simulation, and below or above the median observed valuation multiple α. Each bar reports the share of IPOs in the corresponding category that are high type.



(a) Development stage at IPO, by type



(b) High-type share by market conditions

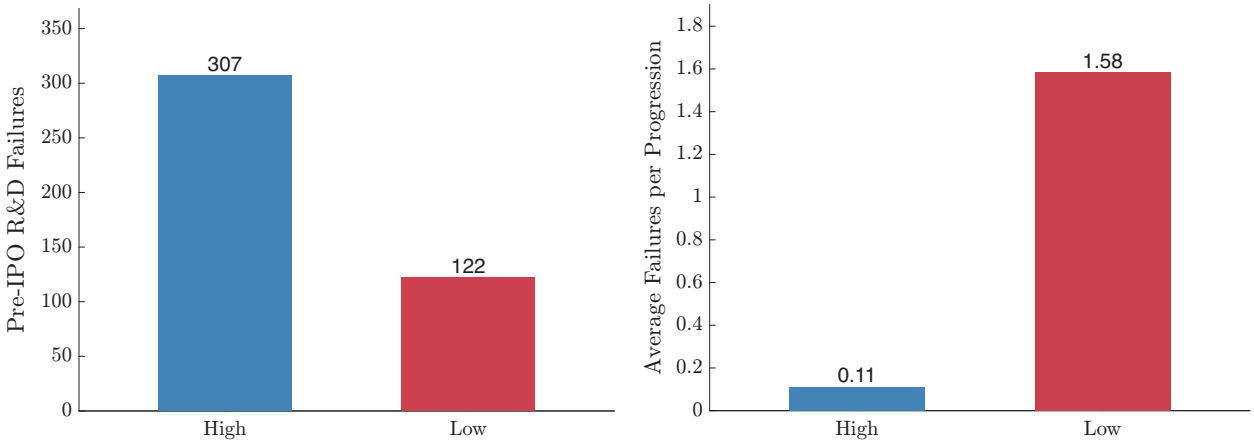
low types are more willing to finance early.

Panel (b) relates this composition to market conditions. A common view is that hot IPO markets worsen adverse selection by drawing more low-quality firms into public markets. The estimated model implies a different mechanism. Favorable market conditions also induce high types to finance, because waiting exposes a more valuable project to liquidation risk. To show this, we split quarters in the simulated sample into above- and below-median groups using two alternative measures of hot-market conditions, the simulated IPO count in the quarter and the observed market valuation multiple *alpha*. The above-median groups correspond to "hot" IPO markets in the simulation. We then plot the average share of IPOs by high-type firms in each group. Consistent with this force, high types account for a modestly larger share of IPOs in quarters with above-median valuation multiples and above-median IPO volume.

Figure 6 illustrates why raw failure counts are not a sufficient statistic for entrepreneur type. Panel (a) shows that simulated high types account for 307 pre-IPO R&D failures, compared with 122 for low types. Thus, in levels, high types generate about 2.5 times as many failures. This does not mean that high types have worse projects. Consistent with the IPO stage distribution, they delay financing and undertake more experimentation, thereby generating more development outcomes, including both progressions and failures. Panel (b) shows the stark contrast after normalizing by experimentation: high types generate only 0.11 failures per milestone progression, compared

Figure 6: Pre-IPO Failures and Entrepreneur Type

Figure 6 shows how simulated high- and low-type entrepreneurs generate pre-IPO development failures in the estimated model. Each entrepreneur is randomly assigned a type according to the estimated type distribution. Conditional on this type and the firm's entry stage, project quality is drawn from the type-contingent posterior implied by the milestones already cleared. Type and project quality then determine the firm's development and financing history through the model's equilibrium strategy. Panel (a) reports the count of pre-IPO experimentation failures by type. Panel (b) normalizes these failures by the number of milestone progressions for each type.



(a) Failures, by type

(b) Failures per progression, by type

with 1.58 for low types. Thus, low types generate more than fourteen times as many failures per progression. The distinction matters for interpretation. In the estimated model, pre-IPO failure hazards reflect both latent project quality and endogenous exposure to experimentation. This is why the pre-IPO failure hazard is informative about the ability gap $\delta = p_0^h - p_0^l$ through the composition channel described in Section 5.3.

6 Value Losses and Policy Implications

6.1 Implications of asymmetric information

We measure the value loss from asymmetric information relative to a symmetric-information benchmark, using the parameters estimated in Section 5. In this benchmark, the entrepreneur's type is common knowledge, although project quality remains unknown and is learned through experimentation. The following lemma characterizes the resulting first-best financing outcome.

Lemma 4. *If the entrepreneur's type is common knowledge, then at every active state* (α, m) *the entrepreneur finances immediately.*

In the asymmetric-information equilibrium, the high type delays financing for experimentation progress, thereby signaling her type to investors. The low type may also delay, though less frequently at early stages, to preserve the possibility of financing later in a pool-to-finance region. Under symmetric information, this signaling motive disappears. Investors observe the entrepreneur's type,

so the financing price reflects the type-contingent assessment of project quality. The only remaining difference between entrepreneurial ownership and investor ownership is liquidity risk. Immediate financing is thus optimal.

The first-best values,

$$v^h(1,\alpha,m) = \pi_I(1,\alpha,m) \qquad \text{and} \qquad v^l(0,\alpha,m) = \pi_I(0,\alpha,m),$$

serve as the benchmark. We then quantify the value gap between the asymmetric-information equilibrium and the first-best outcome. We decompose this gap into two components: the value difference realized at financing, which we call "mispricing," and the value lost when the project is forced into liquidation, which we call "liquidation." Liquidation is a pure value loss for both types. Mispricing, in contrast, reallocates value across types: it generates gains for the low type when she finances at an inflated price and losses for the high type when she finances at a discounted price.

Formally, fix an active state (α, q^-, m) and a type $\theta \in \{h, l\}$, and let $\bar{q}^\theta$ denote the belief that reveals the type, $\bar{q}^h = 1$ and $\bar{q}^l = 0$, so that by Lemma 4 the first-best value is $\pi_I(\bar{q}^\theta, \alpha, m)$. Let τ be the random time at which type θ stops, either by financing or by being liquidated, and let q^f_τ be the posterior belief upon financing. We define the normalized mispricing and liquidation components as the expected discounted losses realized at the stopping time,

$$mp^\theta(\alpha, q^-, m) = \mathbb{E}\Big[\beta^\tau \big(\pi_I(\bar{q}^\theta, \alpha_\tau, m_\tau) - \pi_I(q^f_\tau, \alpha_\tau, m_\tau)\big)\, \mathbf{1}_{\text{Fin}}\Big], \tag{16}$$

$$liq^\theta(\alpha, q^-, m) = \mathbb{E}\Big[\beta^\tau \big(\pi_I(\bar{q}^\theta, \alpha_\tau, m_\tau) + \gamma\big)\, \mathbf{1}_{\text{Liq}}\Big]. \tag{17}$$

Here $\mathbf{1}_{\text{Fin}}$ and $\mathbf{1}_{\text{Liq}}$ are indicators for the two terminal events, financing and liquidation, respectively. The liquidation term values the destroyed project at its first-best price $\pi_I(\bar{q}^\theta, \alpha_\tau, m_\tau)$ and adds the flow cost γ sunk that period, since the entrepreneur pays for continuation before the liquidity shock is realized. The following proposition confirms that each type's value gap can be fully decomposed into mispricing and liquidation, with no residual or interaction term.

Proposition 2. *For every active state (α, q^-, m) and each type $\theta \in \{h, l\}$, the value gap decomposes exactly as*

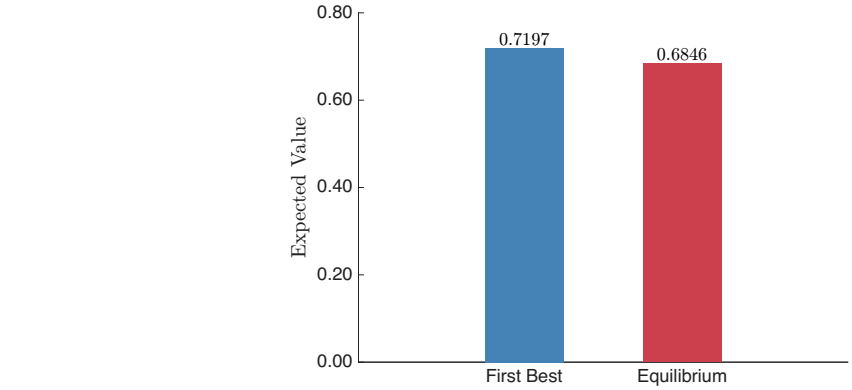
$$\pi_I(\bar{q}^\theta, \alpha, m) - v^\theta(q^-, \alpha, m) = mp^\theta(\alpha, q^-, m) + liq^\theta(\alpha, q^-, m). \tag{18}$$

To quantify the value losses implied by the estimated model, we compute ex-ante expected values for a newly initiated project at $m = 0$. The calculation averages over uncertainty in two steps. First, conditional on the entrepreneur's type, we average the type-specific value over the stationary distribution of the valuation multiple α. Second, we average the resulting high- and low-type values using the estimated prior probabilities. The estimated prior q_0 therefore plays two roles. It determines the ex-ante probability that a new entrepreneur is high type, and, in the asymmetric-information equilibrium, it is also the initial public belief that shapes IPO prices, financing strategies, and the extent of initial mispricing. Figure 7 reports the ex-ante values.

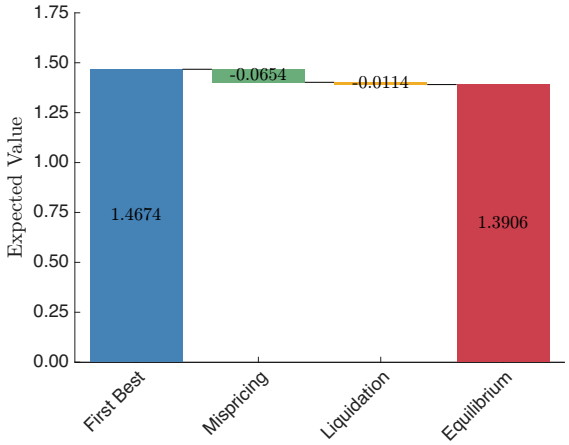
Panel (a) shows that asymmetric information reduces ex-ante project value from 0.720 in the

Figure 7: Value Loss from Asymmetric Information

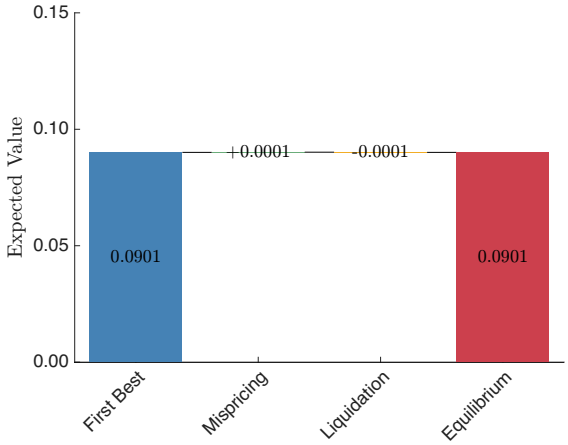
The figure reports ex-ante expected values at the estimated parameters. Panel (a) compares the symmetric-information first-best value with the asymmetric-information equilibrium value. Panels (b) and (c) decompose the type-specific value gap into mispricing and liquidation components.



(a) First best vs. equilibrium



(b) High-type decomposition



(c) Low-type decomposition

first-best benchmark to 0.685 in equilibrium, a loss of 0.035, or 4.9% of the first-best value. Panels (b) and (c) decompose this loss into mispricing and liquidation components for both types.The high type's first-best and equilibrium values are 1.467 and 1.391, respectively, a loss of 0.076, or 5.2% of the first-best value. Panel (b) shows that, for the high type, 85% of the decline is due to mispricing: the high type loses 0.065 from being financed at prices that reflect imperfect investor beliefs, compared with 0.011 from liquidation risk. Because going public while being perfectly revealed as a low type is always an option, the low type's equilibrium value must be weakly higher than her first-best value, thereby offsetting some of the high type's loss in total value. However, in the estimated model, the low type gains slightly from mispricing and loses slightly from liquidation, with the two effects nearly offsetting each other. The value loss therefore falls almost entirely on the high type.

6.2 Policy implications

We next use the estimated model to study how regulatory reforms affect the value losses documented above. Recent policy discussions have emphasized reducing regulatory burdens in drug development, with the goal of accelerating patient access to new therapies, lowering the cost and duration of clinical trials, and strengthening incentives for biomedical innovation. In the model, such reforms can work through distinct margins. The first margin is stage compression. Policies that shorten or consolidate the development process reduce the number of milestones a project must clear before commercialization. We map this type of reform to a reduction in M, the length of the development path. The second margin is a relaxation of the evidentiary standard within each stage. Policies that make it easier for a project to pass a trial or receive approval based on less stringent evidence reduce the probability that a bad project generates a public failure signal. We map this type of reform to a reduction in λ.

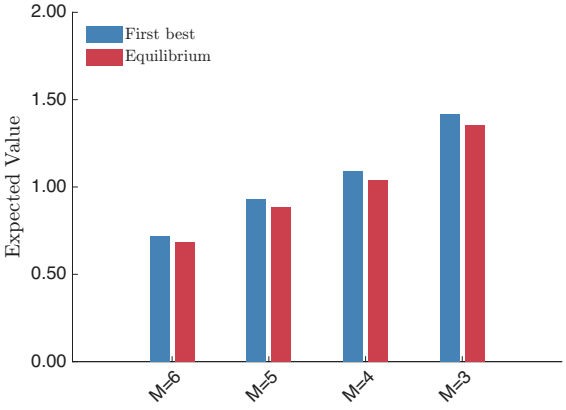
Although both margins reduce regulatory burden, they have different implications for learning, financing, and value. Reducing M shortens the time over which the entrepreneur is exposed to liquidity risk. Reducing λ, by contrast, weakens the screening role of experimentation and may slow the resolution of asymmetric information. We therefore analyze these two counterfactuals separately. For each counterfactual, we recompute the first-best and equilibrium values and decompose the value effects into changes in project first-best value, mispricing, and liquidation. Because the baseline decomposition shows that most of the value loss falls on the high type, we focus in particular on how each policy affects the high-type entrepreneur.

Stage compression We first consider policies and trial designs that shorten the development path. The closest institutional counterpart is a seamless Phase II/III design, which combines the learning objective of Phase II and the confirmatory objective of Phase III within a single study. By replacing two distinct clinical milestones with one integrated protocol, such designs reduce regulatory stand-by time and compress the effective development path. Breakthrough Therapy designation provides a second, broader example. It is intended to expedite the development and review of drugs for serious conditions when preliminary clinical evidence indicates substantial improvement over available therapy. Although this designation does not automatically eliminate a clinical phase, it can reduce the effective number of regulatory steps by coordinating development and review more intensively (Chandra et al., 2026). We capture these forms of stage compression by lowering M while holding fixed the informativeness of each remaining milestone. We implement stage compression by reducing M from the baseline value of six to five, four, and three stages.

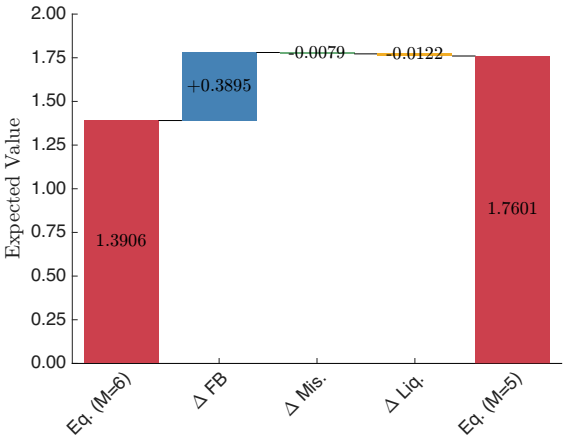
Figure 8 reports the results. Panel (a) shows that both first-best and equilibrium values rise as M falls. Shortening the development path raises project value because the project reaches commercialization after fewer stages, reducing continuation costs and exposure to failure before approval. The increase is quantitatively large: moving from $M = 6$ to $M = 5$ itself increases the first-best value from 0.720 to 0.930, and the equilibrium value from 0.685 to 0.885, a 29% and 29% increase respectively.

Figure 8: Counterfactual Analysis of Stage Compression

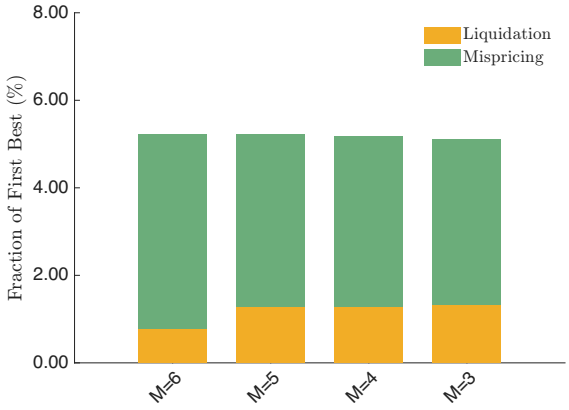
The figure reports the counterfactual effects of reducing the number of development stages M. Panel (a) compares first-best and equilibrium firm values across values of M. Panel (b) decomposes the change in the high-type equilibrium value when M falls from six to five. Panel (c) reports the value loss from asymmetric information as a fraction of the first-best value.



(a) First Best vs. Equilibrium



(b) High-Type Value Change



(c) Loss as Fraction of First Best

Panel (b) decomposes the change in the high-type equilibrium value when M falls from six to five. The high-type value increases from 1.391 to 1.760. Almost all of this gain comes from the increase in the underlying project value, which contributes 0.39. The losses due to mispricing and liquidation are slightly larger in absolute term, increasing by 0.008 and 0.012, respectively. Panel (c), which scales these losses by first-best value, shows that both losses remain roughly constant as a fraction of the first-best value. Mispricing therefore remains the dominant source of value loss, while liquidation remains quantitatively small throughout. Further compression raises equilibrium value mainly by increasing the underlying project value, with little change in the fraction lost due to either friction.

Evidentiary standards We next consider policies that relax the evidentiary standard within a development stage. Institutional examples include greater reliance on surrogate or intermediate

endpoints (Bognar et al., 2017), as well as the new default position to require only a single pivotal trial for approval (Prasad and Makary, 2026). In these cases, the project may advance based on less direct or less repeated evidence of clinical benefit. We implement this counterfactual by varying λ by $\pm 5\%$ and $\pm 10\%$ around its estimated baseline value, holding the number of milestones fixed. Lower values of λ correspond to weaker screening within each stage, while higher values correspond to more informative milestones. This experiment therefore isolates the information effect of regulatory easing from the stage-compression effect studied above.

Figure 9 reports the results. Panel (a) shows that reducing λ lowers both first-best and equilibrium firm values, while increasing λ raises both values. Mechanically, a lower λ raises the probability that a project passes a given milestone, which may at first glance suggest a higher project value. In the model, however, λ also captures the informativeness of successful experimentation: a low λ makes a successful milestone convey less good news about project quality. The project is therefore more likely to continue even when its latent quality is poor, consuming additional development costs and delaying the resolution of quality uncertainty. The value of experimentation comes precisely from its ability to identify and terminate bad projects early, so lowering λ weakens this screening mechanism.

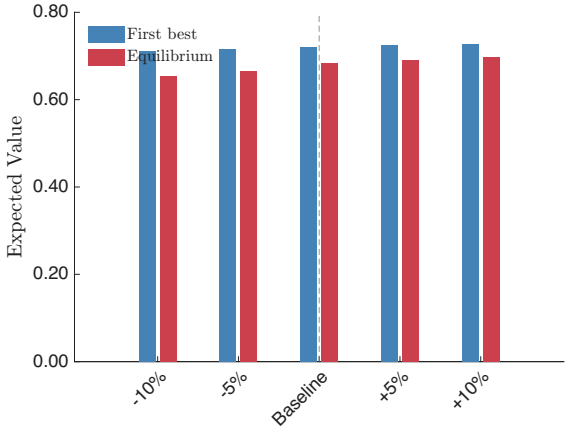
The equilibrium firm value falls even more because the same force worsens the financing friction. When successful milestones become less informative, investors learn more slowly from experimentation outcomes. The high type therefore remains pooled with the low type for longer and faces a larger pricing loss when financing occurs. Thus, reducing λ amplifies the asymmetric information problem. Panel (b) demonstrates this effect by showing how the high-type equilibrium value changes when λ falls by 10%. The high-type value decreases from 1.391 to 1.343. Unlike the stage-compression counterfactual, the main effect is not a change in the underlying project value. The change in underlying project first-best value accounts for only 0.003, or 6% of the total decline. Instead, most of the decline comes from mispricing, which contributes -0.038 (79%), while liquidation contributes an additional -0.007 (15%). These changes indicate that weakening the evidentiary standard worsens the high type's financing problem. She faces a larger pricing loss when she finances because the market is slower to learn her type, which also creates further incentives to delay for more experimentation signals and exacerbates liquidation risk. Consistent with this, Panel (c) expresses the value loss as a fraction of the first-best value. The fraction lost to asymmetric information increases as λ falls and decreases as λ rises. Mispricing remains the dominant component of the loss, while liquidation is smaller throughout.

The comparison with stage compression is the main economic lesson. Reducing M shortens the development path while preserving the informativeness of each remaining milestone. Reducing λ instead weakens the information produced by each milestone. The two policies therefore have opposite effects on the information environment, and hence on entrepreneur value.

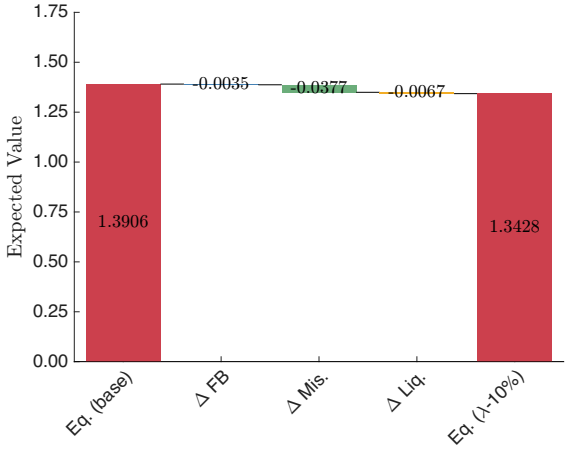
Development-cost intensity We finally consider changes in the cost intensity of experimentation. It first captures changes in the business environment of drug development: industry discus-

Figure 9: Counterfactual Analysis of Evidentiary Standards

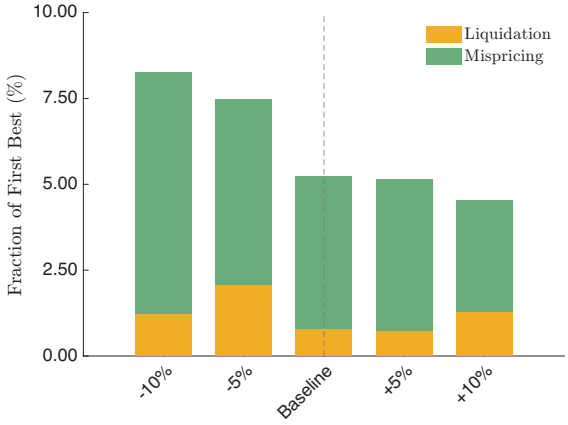
The figure reports the counterfactual results of changing the bad-news probability λ. Panel (a) compares first-best and equilibrium firm values as λ varies by $\pm 5\%$ and $\pm 10\%$ around the baseline. Panel (b) decomposes the change in the high-type equilibrium value when λ falls by 10%. Panel (c) reports the value loss from asymmetric information as a fraction of the first-best value.



(a) First Best vs. Equilibrium



(b) High-Type Value Change



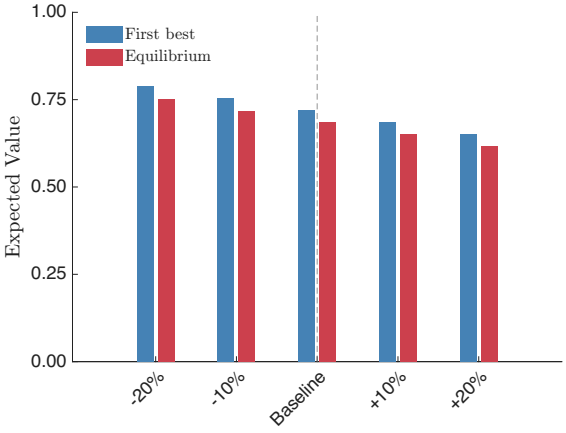
(c) Loss as Fraction of First Best

sions often emphasize that drug development has become more expensive as trials become larger, longer, and more complex. This counterfactual also captures policies that reduce the effective cost of conducting a given trial. Examples include R&D tax credits, orphan-drug clinical-testing credits, and other cost-sharing programs that lower the after-tax or out-of-pocket cost of experimentation (Yin, 2008). Decentralized trial elements have a similar interpretation: by allowing trial-related activities to occur remotely or at convenient locations, including telehealth visits, in-home visits, and local-provider visits, they can reduce the operational cost of producing clinical evidence (DiMasi et al., 2023). We implement this counterfactual by varying γ by $\pm 10\%$ and $\pm 20\%$ around its estimated baseline value.

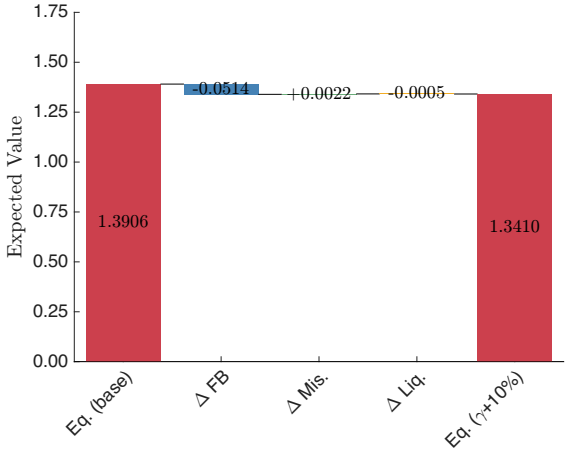
Figure 10 reports the results. Panel (a) shows that both first-best and equilibrium firm values decline as γ increases. This is the direct cost effect—higher development costs reduce the value

Figure 10: Counterfactual Analysis of Development-Cost Intensity

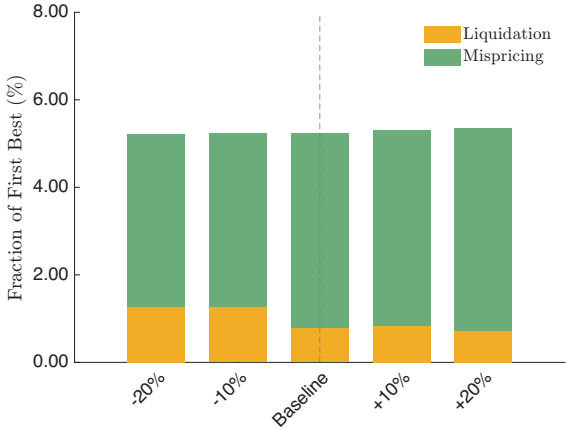
The figure reports the counterfactual results of changing the development-cost intensity γ. Panel (a) compares first-best and equilibrium firm values as γ varies by $\pm 10\%$ and $\pm 20\%$ around the baseline. Panel (b) decomposes the change in the high-type equilibrium value when γ rises by 10%. Panel (c) reports the value loss from asymmetric information as a fraction of the first-best value.



(a) First Best vs. Equilibrium



(b) High-Type Value Change



(c) Loss as Fraction of First Best

of completing a project under both symmetric and asymmetric information. Panel (b) decomposes the change in the high-type equilibrium value when γ rises by 10%. The high-type value falls from 1.391 to 1.341. Almost all of this decline comes from the reduction in the underlying project value, which contributes -0.051. The changes in mispricing and liquidation are small by comparison, contributing 0.002 and -0.001, respectively. Panel (c) expresses the value loss as a fraction of first-best value. The fraction lost to asymmetric information is nearly flat across the counterfactual range. These changes indicate that increasing γ primarily lowers the profitability of experimentation rather than substantially changing the financing friction. This flatness reflects that γ is a weak screening tool: it changes overall project profitability, but not the informativeness of experimentation, limiting its ability to mitigate mispricing.

Note that the three counterfactuals are partial-equilibrium exercises that measure firm value

rather than total social welfare. Stage compression may accelerate market entry and give patients earlier access to new therapies, generating consumer surplus beyond the gains captured by the model. Conversely, weaker evidentiary standards may increase the approval of ineffective or unsafe drugs, a health cost the model omits. Accounting for this cost would reinforce, rather than overturn, our conclusion that weaker standards are costly. In this paper, our objective is instead to isolate how these policy changes reshape the information environment that biotech firms face when financing innovation. Accordingly, we focus on firm value rather than total social welfare. Extending the current framework to incorporate consumer surplus is an important avenue for future research.

7 Conclusions

We study how firms time external financing while experimentation reveals project quality and entrepreneurial ability. We assemble a data set of drug-development histories linked to IPO records for U.S. biotech firms and document three patterns. First, the development stage at listing predicts the success of drugs initiated after the IPO. Second, private firms are liquidated for reasons largely unrelated to their own experimentation outcomes. Third, listing responds to public-market valuations, whereas liquidation does not. We then structurally estimate a dynamic model in which entrepreneurs privately know their ability, experimentation publicly reveals both ability and project quality, and waiting generates information but exposes the project to liquidation risk and time-varying market valuations. We find that adverse selection reduces ex ante project value by 4.9%, with the loss falling almost entirely on high-ability entrepreneurs, who experiment the longest. Counterfactuals show that shortening development and weakening evidentiary standards are not equivalent: removing a milestone while preserving the informativeness of the remaining milestones raises equilibrium value by 29%, whereas less informative milestones slow investor learning and reduce high-type value.

Several aspects of our analysis warrant discussion. First, although we refer to the private type as entrepreneurial ability, it admits a broader interpretation. It may capture not only the capabilities of a firm's founders and scientists but also the technological soundness of its drug-development platform. For example, a high-type firm may possess specialized expertise in GLP-1 biology or PD-1 checkpoint inhibition, making its drug candidates more likely to to be viable than outside investors can infer ex ante. Under this interpretation, IPO timing signals the privately known strength of the firm's scientific platform. Second, our estimates are specific to biotech. The mechanism requires a public, staged record of experimentation, a feature that few industries provide as clearly. The underlying trade-off between learning and financing delay is more general, and we hope future work can quantify it in other settings.

References

Aghamolla, C. and R. T. Thakor (2022): "IPO peer effects," *Journal of Financial Economics*, 144, 206–226.

Andrews, I., M. Gentzkow, and J. M. Shapiro (2017): "Measuring the Sensitivity of Parameter Estimates to Estimation Moments," *Quarterly Journal of Economics*, 132, 1553–1592.

——— (2020): "Transparency in Structural Research," *Journal of Business & Economic Statistics*, 38, 711–722.

Arnoud, A., F. Guvenen, and T. Kleineberg (2019): "Benchmarking global optimizers," Working paper, National Bureau of Economic Research.

Banks, J. S. and J. Sobel (1987): "Equilibrium selection in signaling games," *Econometrica: Journal of the Econometric Society*, 647–661.

Benmelech, E., J. Eberly, D. Papanikolaou, and J. Krieger (2021): "Private and social returns to R&D: drug development and demographics," in *AEA Papers and Proceedings*, vol. 111, 336–340.

Benveniste, L. M., W. Y. Busaba, and W. J. Wilhelm Jr (2002): "Information externalities and the role of underwriters in primary equity markets," *Journal of Financial Intermediation*, 11, 61–86.

Bognar, K., J. A. Romley, J. P. Bae, J. Murray, J. W. Chou, and D. N. Lakdawalla (2017): "The role of imperfect surrogate endpoint information in drug approval and reimbursement decisions," *Journal of Health Economics*, 51, 1–12.

Bryan, K. A. and H. L. Williams (2021): "Innovation: Market failures and public policies," in *Handbook of industrial organization*, ed. by K. Ho, A. Hortaçsu, and A. Lizzeri, Amsterdam, the Netherlands: North-Holland, vol. 5 of *Handbook of Industrial Organization, Volume 5*, 281–388.

Budish, E., B. N. Roin, and H. Williams (2015): "Do firms underinvest in long-term research? Evidence from cancer clinical trials," *American Economic Review*, 105, 2044–85.

Bustamante, M. C. (2012): "The dynamics of going public," *Review of Finance*, 16, 577–618.

Carter, R. and S. Manaster (1990): "Initial public offerings and underwriter reputation," *Journal of Finance*, 45, 1045–1067.

Celentano, F. and M. Rempel (2026): "Public listing choice with persistent hidden information," *Review of Economic Studies*, 93, 833–891.

Celik, M. A., X. Tian, and W. Wang (2022): "Acquiring Innovation under Information Frictions," *Review of Financial Studies*, 35, 4474–4517.

Chandra, A., J. Kao, K. L. Miller, and A. D. Stern (2026): "Regulatory incentives for innovation: the FDA's breakthrough therapy designation," *Review of Economics and Statistics*, 108, 470–484.

Chemmanur, T. J. and P. Fulghieri (1999): "A theory of the going-public decision," *Review of Financial Studies*, 12, 249–279.

Cho, I.-K. and D. M. Kreps (1987): "Signaling games and stable equilibria," *Quarterly Journal of Economics*, 102, 179–221.

Cornelli, F. and D. Goldreich (2003): "Bookbuilding: How informative is the order book?" *Journal of finance*, 58, 1415–1443.

Cunningham, C., F. Ederer, and S. Ma (2021): "Killer acquisitions," *Journal of Political Economy*, 129, 649–702.

Cziraki, P. and D. Jenter (2022): "The market for CEOs," Working paper, European Corporate Governance Institute.

Daley, B. and B. Green (2012): "Waiting for news in the market for lemons," *Econometrica*, 80, 1433–1504.

——— (2016): "An information-based theory of time-varying liquidity," *Journal of Finance*, 71, 809–870.

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

DiMasi, J. A., R. W. Hansen, and H. G. Grabowski (2003): "The price of innovation: New estimates of drug development costs," *Journal of Health Economics*, 22, 151–185.

DiMasi, J. A., Z. Smith, I. Oakley-Girvan, A. Mackinnon, M. Costello, P. Tenaerts, and K. A. Getz (2023): "Assessing the financial value of decentralized clinical trials," *Therapeutic Innovation & Regulatory Science*, 57, 209–219.

Doidge, C., G. A. Karolyi, and R. M. Stulz (2017): "The US listing gap," *Journal of Financial Economics*, 123, 464–487.

Erickson, T. and T. M. Whited (2002): "Two-step GMM estimation of the errors-in-variables model using high-order moments," *Econometric Theory*, 18, 776–799.

Ewens, M. and J. Farre-Mensa (2020): "The deregulation of the private equity markets and the decline in IPOs," *Review of Financial Studies*, 33, 5463–5509.

Ewens, M., R. Nanda, and M. Rhodes-Kropf (2018): "Cost of experimentation and the evolution of venture capital," *Journal of Financial Economics*, 128, 422–442.

Feng, F. Z., T. Nohel, X. Tian, W. Wang, and Y. Wu (2026): "The Incentives of SPAC Sponsors," *Journal of Financial Economics*, 177, 104220.

Fuchs, W., B. Green, and D. Papanikolaou (2016): "Adverse selection, slow-moving capital, and misallocation," *Journal of Financial Economics*, 120, 286–308.

Gao, X., J. R. Ritter, and Z. Zhu (2013): "Where have all the IPOs gone?" *Journal of Financial and Quantitative Analysis*, 48, 1663–1692.

Gompers, P. A., W. Gornall, S. N. Kaplan, and I. A. Strebulaev (2020): "How do venture capitalists make decisions?" *Journal of Financial Economics*, 135, 169–190.

Grenadier, S. R. and A. Malenko (2011): "Real options signaling games with applications to corporate finance," *Review of Financial Studies*, 24, 3993–4036.

Guedj, I. and D. S. Scharfstein (2004): "Organizational scope and investment: Evidence from the drug development strategies and performance of biopharmaceutical firms," Working Paper, National Bureau of Economic Research.

Guenzel, M. and T. Liu (2026): "Excess commitment in R&D," *Review of Financial Studies*, 39, 2179–2221.

Guo, X., P. Ottonello, T. Winberry, and T. M. Whited (2025): "Firm heterogeneity and adverse selection in external finance: Micro evidence and macro implications," Working paper, National Bureau of Economic Research.

Hall, B. H. and J. Lerner (2010): "The financing of R&D and Innovation," in *Handbook of the Economics of Innovation*, ed. by B. H. Hall and N. Rosenberg, Amsterdam, the Netherlands: North-Holland, vol. 1, 609–39.

Hanley, K. W. and G. Hoberg (2010): "The information content of IPO prospectuses," *Review of Financial Studies*, 23, 2821–2864.

Hong, H., A. Mahajan, and D. Nekipelov (2015): "Extremum estimation and numerical derivatives," *Journal of Econometrics*, 188, 250–263.

Kaplan, S. N., B. A. Sensoy, and P. Strömberg (2009): "Should investors bet on the jockey or the horse? Evidence from the evolution of firms from early business plans to public companies," *Journal of Finance*, 64, 75–115.

Kaplan, S. N. and M. Sorensen (2021): "Are CEOs Different?" *Journal of Finance*, 76, 1773–1811.

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

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

Krieger, J. L., X. Li, and R. T. Thakor (2022b): "Find and replace: R&D investment following the erosion of existing products," *Management Science*, 68, 6552–71.

Lerner, J., H. Shane, and A. Tsai (2003): "Do equity financing cycles matter? Evidence from biotechnology alliances," *Journal of Financial Economics*, 67, 411–446.

Li, X., T. Liu, and L. A. Taylor (2023): "Common ownership and innovation efficiency," *Journal of Financial Economics*, 147, 475–497.

Li, X., S. Wang, J. Xu, and X. Zheng (2024): "How Does VC Engagement Direct Startup Experimentation?" Working paper, Columbia Business School.

Lo, A. W. and R. T. Thakor (2022): "Financing biomedical innovation," *Annual Review of Financial Economics*, 14, 231–270.

Loughran, T. and B. McDonald (2013): "IPO first-day returns, offer price revisions, volatility, and form S-1 language," *Journal of Financial Economics*, 109, 307–326.

Lowry, M., M. S. Officer, and G. W. Schwert (2010): "The variability of IPO initial returns," *Journal of Finance*, 65, 425–465.

Lowry, M. and G. W. Schwert (2002): "IPO market cycles: Bubbles or sequential learning?" *Journal of Finance*, 57, 1171–1200.

McFadden, D. (1989): "A method of simulated moments for estimation of discrete response models without numerical Integration," *Econometrica*, 57, 995–1026.

Megginson, W. L. and K. A. Weiss (1991): "Venture capitalist certification in initial public offerings," *Journal of Finance*, 46, 879–903.

Michaely, R. and W. H. Shaw (1994): "The pricing of initial public offerings: Tests of adverse-selection and signaling theories," *Review of Financial Studies*, 7, 279–319.

Morellec, E. and N. Schürhoff (2011): "Corporate investment and financing under asymmetric information," *Journal of financial Economics*, 99, 262–288.

Nikolov, B., L. Schmid, and R. Steri (2021): "The sources of financing constraints," *Journal of Financial Economics*, 139, 478–501.

Pakes, A. and D. Pollard (1989): "Simulation and the asymptotics of optimization estimators," *Econometrica*, 57, 1027–1057.

Pástor, L., L. A. Taylor, and P. Veronesi (2009): "Entrepreneurial learning, the IPO decision, and the post-IPO drop in firm profitability," *Review of Financial Studies*, 22, 3005–3046.

Phillips, G. M. and A. Zhdanov (2013): "R&D and the incentives from merger and acquisition activity," *Review of Financial Studies*, 26, 34–78.

Prasad, V. and M. A. Makary (2026): "One pivotal trial, the new default option for FDA approval—ending the two-trial dogma," *New England Journal of Medicine*, 394, 815–817.

Robinson, D. T. and T. E. Stuart (2007): "Financial contracting in biotech strategic alliances," *Journal of Law and Economics*, 50, 559–596.

Sertkaya, A., T. Beleche, A. Jessup, and B. D. Sommers (2024): "Costs of drug development and research and development intensity in the US, 2000-2018," *JAMA network open*, 7, e2415445.

Strebulaev, I. A., H. Zhu, and P. Zryumov (2016): "Optimal issuance under information asymmetry and accumulation of cash flows," Working paper, Rock Center for Corporate Governance at Stanford University.

Subrahmanyam, A. and S. Titman (1999): "The going-public decision and the development of financial markets," *Journal of Finance*, 54, 1045–1082.

Tauchen, G. (1986): "Finite state Markov-chain approximations to univariate and vector autoregressions," *Economics Letters*, 20, 177–181.

Thakor, R. T., N. Anaya, Y. Zhang, C. Vilanilam, K. W. Siah, C. H. Wong, and A. W. Lo (2017): "Just how good an investment is the biopharmaceutical sector?" *Nature biotechnology*, 35, 1149–1157.

Wong, C. H., K. W. Siah, and A. W. Lo (2019): "Estimation of clinical trial success rates and related parameters," *Biostatistics*, 20, 273–286.

Yin, W. (2008): "Market incentives and pharmaceutical innovation," *Journal of Health Economics*, 27, 1060–1077.

Yung, C., G. Çolak, and W. Wang (2008): "Cycles in the IPO market," *Journal of Financial Economics*, 89, 192–208.

Zryumov, P. (2015): "Dynamic adverse selection: Time-varying market conditions and endogenous entry," Working paper, University of Rochester.

Internet Appendix

Financing Experimentation

Not For Publication

A Data and Estimation Appendix

A.1 Additional detail on projecting lead-drug average annual sales

We project each firm's lead drug average annual worldwide sales in two stages. We first construct a regression-based estimate for every lead drug and then combine it with an EvaluatePharma analyst forecast when one is available.

First stage: category-by-event-year regression We begin with the universe of Cortellis drugs for which annual worldwide sales are recorded. Using the Cortellis-to-ICD-9 crosswalk of Li et al. (2023), we link each drug's indications to their second-level ICD-9 therapeutic categories. The sales records contain realized historical sales for launched drugs and Cortellis forward projections for drugs still under development. We use both sources to estimate the following regression for each drug d and post-launch event year τ (where $\tau = 1$ is the first year of sales), we estimate

$$\text{Sales}_{d,\tau} \;=\; \alpha + \sum_{k} \beta_k \, \mathbf{1}\{d \in \text{ICD}_k\} \;+\; \gamma_\tau \;+\; \varepsilon_{d,\tau}, \tag{19}$$

where $\mathbf{1}\{d \in \text{ICD}_k\}$ indicates whether drug d targets second-level ICD-9 category k, and γ_τ is an event-year fixed effect. We truncate the sample at $\tau \leq 10$ to account for the patent cliff and express sales in 2017 dollars using the GDP deflator. The coefficients $\{\beta_k\}$ capture the average annual revenue contribution of each therapeutic category during the first post-launch decade.

For each lead drug ℓ in our sample, we predict its event-τ sales as

$$\widehat{\text{Sales}}_{\ell,\tau} \;=\; \widehat{\alpha} \;+\; \sum_{k \in \mathcal{K}_\ell} \widehat{\beta}_k \;+\; \widehat{\gamma}_\tau,$$

where $\mathcal{K}_\ell$ is the set of second-level ICD-9 categories associated with the lead drug's indications. If Cortellis directly records sales for drug ℓ in event year τ, we use the recorded value instead of the regression prediction. We use $\widehat{\text{Sales}}_{\ell,\tau}$ only when no recorded value is available. We then average this series of recorded and imputed values over $\tau = 1, \ldots, 10$ to obtain the first-stage projection of the lead drug's average annual sales.

Second stage: blending with EvaluatePharma When an EvaluatePharma analyst forecast is available, we first average its projected post-launch sales trajectory across years. We then combine that average with the first-stage projection using equal weights. Both measures are converted to 2017 dollars with the GDP deflator before they are combined. If no EvaluatePharma forecast is available, we retain the first-stage projection. This procedure balances the broader analyst coverage and higher variance of the EvaluatePharma forecasts against the more systematic but coarser regression-based estimate. We exclude lead drugs with nonpositive projected sales.

A.2 Solving the model

For each candidate parameter vector $\theta = (\delta, p_0^l, q_0, \lambda, \kappa, \gamma)$, we set $p_0^h = p_0^l + \delta$, hold the remaining parameters at the calibrated values in Table 6, and solve the equilibrium of Section 4.3 numerically on a discretized state space.

Discretization We approximate the AR(1) process for the biotech-sector valuation multiple in Equation (3) with a finite-state Markov chain using the method of Tauchen (1986). The approximation uses $N_\alpha = 50$ grid points spanning 2.5 unconditional standard deviations on either side of the unconditional mean, yielding the grid $\{\alpha_1, \ldots, \alpha_{N_\alpha}\}$ and transition matrix P_α. We discretize the public belief q^- on an equally spaced grid over $[0, 1]$ with a step size of 0.001, yielding 1,001 belief nodes. The development stage m is already discrete.

The financing price We first compute the investors' zero-profit price $\pi_I(q, \alpha, m)$ over the full state space. Although Lemma 3 provides a closed form for π_I, we solve Equation (9) directly instead of evaluating the coefficients (a_m, b_m, c_m). For a fixed (q, m), stacking prices across the α grid yields the linear system

$$\big[I - \beta(1-\eta_m)P_\alpha\big]\,\pi_I(\cdot, m, q) = \beta\eta_m\big(1 - \lambda(1 - p_m(q))\big)\,P_\alpha\,\pi_I(\cdot, m+1, q_+) - \gamma\mathbf{1},$$

which we solve backward from the terminal condition $\pi_I(\cdot, M, q) = \alpha$, where q_+ denotes the milestone update of q in Equation (6). Solving this system directly eliminates the approximation error that the truncated Tauchen grid would introduce into conditional expectations of α_{t+1} when iterating on the closed form.

The high type's cutoff Step 1 of the proof of Proposition 1 reduces the high type's indifference condition to $\pi_I(q^-, \alpha, m) = (1-\kappa)\pi_I(1, \alpha, m) - \kappa\gamma$. For each belief-stage pair, we set $\alpha_h^\star(q^-, m)$ equal to the lowest point on the α grid at which the financing price weakly exceeds this separating continuation value. If no such point exists, the high type never finances at that state, and the pool-to-finance region is empty. At or above the cutoff, both types finance, and the high type's value equals the financing price.

The low type's cutoff and mixing probability Given the high type's cutoff, we solve the low type's problem by backward induction across stages and, within each stage, across the belief grid. Because the milestone update in Equation (6) generally falls between grid nodes, we obtain continuation values by linearly interpolating between adjacent belief points. At each (q^-, m), we search over candidate values of $\alpha_l^\star(q^-, m)$ on the α grid while imposing monotonicity of the cutoff across belief levels. If the candidate cutoff is at the bottom of the grid, there is no waiting region. We then construct the low type's value function from the separating region, where she receives $\pi_I(0, \alpha, m)$, and the pooling region above $\alpha_h^\star$, where she receives $\pi_I(q^-, \alpha, m)$. If the candidate cutoff lies strictly above the bottom of the grid, we solve the corresponding linear system for the

low type's value in the waiting region and concatenate the three regions. We accept a candidate when it satisfies the indifference condition Equation (12).

When the accepted low-type cutoff lies strictly below the high-type cutoff, a semipooling region arises on $[\alpha_l^\star, \alpha_h^\star)$. For each α in this region, we identify the posterior $Q^\star$ consistent with low-type mixing. It is the smallest belief node at which the low type's expected continuation value from waiting weakly exceeds $\pi_I(0, \alpha, m) + \gamma$. We then recover the mixing probability $p(\alpha, q^-, m)$ by inverting Equation (13) and use the resulting posterior to construct the high type's continuation value in that region.

The high type's value outside the financing region When the low-type cutoff lies weakly above the high-type cutoff, the equilibrium below $\alpha_h^\star$ is pooling, and we obtain the high type's value by solving the corresponding linear system. When a semipooling region exists, we evaluate her continuation value at the posterior $Q^\star$ defined above and recover her value at lower valuations recursively. At the boundary belief $q = 1$, the market treats every entrepreneur as a high type. By Lemma 4, all firms then finance immediately, and the value function equals $\pi_I(1, \alpha, m)$ throughout.

The routine returns the value and policy functions for both types, the two cutoff surfaces, the α grid, and the price array π_I. These objects are used in the simulation and in the counterfactuals of Section 6.

A.3 Simulating the model

We simulate the model along the observed firm-quarter panel rather than in an artificial economy. Entry dates, entry stages, and the realized path of the aggregate valuation multiple therefore come directly from the data.

Random draws We generate six mutually independent random-number streams with fixed seeds, one for each of the following: the entrepreneur's type, the project's latent quality, the financing decision, the liquidity shock, the arrival of a development outcome, and the pass-or-fail realization conditional on arrival. The moments remain nonsmooth in θ for the reason discussed in Online Appendix A.4. We discard a burn-in of 10,000 draws from each stream before using the retained sequence. A firm is assigned the low type if its type draw exceeds q_0.

We draw project quality separately from type because the entrepreneur's type determines only the prior probability that her project is good, not its realized quality. Project quality is drawn at entry and remains fixed thereafter. A firm whose lead drug is first observed at stage s_0 has already passed s_0 trials. Because each pass is good news about quality, we draw its project as good with the survival-updated probability $p_{s_0}^\theta$ in Equation (1), rather than with the unconditional prior p_0^θ.

Firm histories Each firm's simulated path begins in its first observed quarter at the observed lead-drug stage and with public belief q_0. In each quarter, the state consists of the current stage, the current belief, and the biotech price-to-sales ratio observed in that calendar quarter. We

obtain the equilibrium financing probabilities s^h and s^l from the solved policy functions by bilinear interpolation over the valuation and belief dimensions. If the realized multiple falls outside the Tauchen grid, we evaluate the policy at the nearest endpoint. At the terminal stage $m = M$, both types finance with probability one by construction.

Given s^h and s^l, we form the posteriors in Equation (4) and Equation (5) using Bayes' rule. If the prior is degenerate or both types follow the same policy, both posteriors equal the prior. The waiting posterior q^w governs the continuation of the private path and is updated again through Equation (6) after a milestone advance. The financing posterior q^f determines the transaction price. The simulated IPO valuation is $\pi_I(q^f, \alpha_t, m)$, interpolated across adjacent belief nodes and evaluated at the nearest point on the valuation grid. At the terminal stage, it equals the realized multiple. Thus, the price is interpolated only over beliefs, whereas the policy functions are interpolated over both beliefs and valuations.

Events within the quarter follow the timing convention in Figure 2. A liquidity shock occurs with probability κ, and a development outcome arrives with probability η_m. Conditional on a development outcome, a good project always advances, while a bad project fails with probability λ and otherwise advances, as in Section 4. Outcomes depend on the project's latent quality rather than the entrepreneur's type. A bad project led by a high-ability entrepreneur fails at the same rate as one led by a low-ability entrepreneur; the types differ only in the probability that their projects are good. Type affects the simulated history through the financing policy, s^h or s^l, and through the prior used to draw project quality. A firm's simulated history ends at the first occurrence of financing, failure, or liquidation ,if any. Otherwise, it is right censored at the last-observed calendar quarter, i.e. 2020Q4.

From histories to moments We first collapse the simulated panel to the firm level, recording each firm's first financing quarter and the associated valuation and development stage.We compute four of the eight targeted moments in Table 7 directly from these records: the mean IPO valuation, the variance and skewness of the stage at IPO, and the share of IPOs at Phase III or later. The failure and liquidation moments are quarterly hazards rather than firm-level averages. For each event, the numerator is the number of firms experiencing either event before financing, and the denominator is the total number of post-entry quarters during which firms are at risk. We exclude each firm's entry quarter from the denominator because firms enter as alive, exactly matching the empirical construction.

We compute the two progression moments from the simulated stage path. The share of firms ever reaching Phase II is the fraction of entering firms whose simulated stage reaches $m \geq 2$ at any point. The quarterly progression rate is the mean stage-advance indicator across all firm-quarters, matching the construction of its empirical counterpart. It is one of three targeted moments defined as ratios of firm-quarter totals rather than firm-level averages, along with the two exit hazards. A simulated history ends at financing, failure, or liquidation, whereas the observed panel retains every quarter in which the firm appears in the data. Consequently, observed quarters after a simulated

exit enter the denominator of the progression rate as quarters without an advance.

A.4 The SMM criterion and numerical optimization

Empirical moments and the weighting matrix We compute the empirical moments from the same firm-quarter panel used in the simulation. The weighting matrix is the inverse of the estimated covariance matrix of the eight moments. We construct this covariance matrix from firm-level influence functions, treating firms rather than firm-quarters as the units of independent variation. For a mean, the influence function is the firm's deviation from the sample mean; for a rate, it is the firm's indicator minus the sample proportion; and for a variance, it is the squared deviation minus the sample variance. Two moments require additional care. For the skewness of the stage at IPO, $\hat{\Gamma} = \hat{\mu}_3/\hat{\sigma}^3$, the naive cubic deviation misstates covariances because the mean and variance are themselves estimated. In standardized units $z_i = (x_i - \hat{\mu})/\hat{\sigma}$, the appropriate influence function is

$$\psi_i = z_i^3 - 3z_i - \tfrac{3}{2}\hat{\Gamma} z_i^2 + \tfrac{1}{2}\hat{\Gamma},$$

which reduces to $z^3 - 3z$ under normality and yields the textbook variance $6/n$. Three moments, the quarterly progression rate and the two exit hazards, are ratios of firm-quarter sums, $g = \sum_i s_i / \sum_i n_i$, rather than firm-level averages. For each, the delta method gives the firm-level influence function $(s_i - g\, n_i)/\bar{n}$, where n_i is the firm's number of contributing quarters and $\bar{n}$ is its sample mean. Moments defined only for firms that go public are treated as missing for all other firms. Each covariance-matrix entry is the sample mean of the product of the two relevant influence functions among firms for which both are observed. The resulting matrix is symmetric and positive definite, so $W = \hat{\Omega}^{-1}$ is well defined.

The equilibrium-collapse gate In some regions of the parameter space, particularly when development costs are high and project priors are low, the financing price is negative at every valuation state. The equilibrium then degenerates to a corner in which no project is financed. Because the moments remain finite in these regions, an unconstrained optimizer may be drawn toward them. At each candidate θ, we therefore test whether $\max_\alpha \pi_I(\alpha, m, q = 0) < 0$ for any stage m and assign a large penalty if it does. We evaluate the condition at $q = 0$ because $\pi_I(\cdot, \cdot, 0)$ is the lower envelope of the price and the low type's separating value in Step 3 of Online Appendix A.2. If this value is negative at every valuation state, the construction in that step has no admissible outside option. This gate allows us to retain wide parameter bounds without admitting degenerate solutions.

The numerical Jacobian The sensitivity matrix in Section 5.3, the asymptotic standard errors, and the J-statistic all require $G = \partial m^s(\theta)/\partial\theta'$ evaluated at $\hat{\theta}$. Asymptotic theory requires the Jacobian of the limiting moment function, which is smooth, but the numerical function we can evaluate is not. We solve the equilibrium on a 50-point valuation grid and a 1,001-point belief grid.

The simulated moments are therefore step functions of θ and change only when a perturbation moves a cutoff across a grid node. A standard finite difference is consequently unreliable.

We instead evaluate each parameter at 25 points: the estimate itself and 24 perturbations evenly spaced over a $\pm 2.5\%$ window around it, holding the other five parameters fixed. For each simulated moment, we estimate the derivative as the slope coefficient from a local linear regression of the moment on the parameter across these points. The window width is the main discretionary choice and reflects a tradeoff. If the window is too wide, the estimated slope averages over curvature in the moment function rather than approximating the derivative at the estimate. If it is too narrow, the solver's discretization error can dominate: over a half-width h, an error of magnitude ϵ can induce a spurious slope of order ϵ/h. Because such noise inflates $G'WG$, it can lead to artificially small implied standard errors rather than simply appearing as sampling noise. We use a $\pm 2.5\%$ window, which provides a reasonable balance between these two considerations.

Expressing the two exit moments as quarterly hazards also removes a degeneracy in the earlier fixed-horizon construction. Under that construction, the one-year bankruptcy rate was *exactly* constant across the full sweeps of δ, p_0^l, and γ, making three elements of G structurally zero rather than merely small. Under the hazard construction, no element of G is exactly zero, and each targeted moment responds to every parameter somewhere within the window.

Optimization The criterion in Equation (15) is minimized subject to the bounds

$$0.04 \le \delta \le 0.70, \quad 0.10 \le p_0^l \le 0.70, \quad 0.40 \le q_0 \le 0.90,$$
$$0.20 \le \lambda \le 0.90, \quad 0.0005 \le \kappa \le 0.015, \quad 0.001 \le \gamma \le 0.035,$$

using the three-stage tiktak algorithm (Arnoud et al., 2019). In the first stage, we draw 10,000 starting points from a Halton sequence over the six-dimensional parameter space and run a bounded Nelder–Mead search from each point. We screen out starting points that trigger the collapse gate before beginning the search. In the second stage, we collect the best point from each of 500 blocks of twenty starts and retain the 100 points with the lowest criterion values. We refine these points in a single sequential chain initialized at the best of the 100. Proceeding from the worst candidate to the best, each step begins a new bounded Nelder–Mead search from a convex combination of the current candidate and the incumbent. The weight on the incumbent increases according to a logistic schedule, and the incumbent is updated whenever the search finds an improvement. In the third stage, we refine the best point from the second stage using a budget of 5,000 evaluations and convergence tolerances of 10^{-6} for both the parameter vector and the criterion.

A.5 Local sensitivity of the estimates to the targeted moments

This appendix develops the local sensitivity analysis summarized in Section 5.3. Two objects underlie it: the Jacobian of the simulated moments with respect to the parameters, and the sensitivity

Table IA.1: Sensitivity of the Estimates to the Targeted Moments

This table reports the sensitivity of the structural estimates to the targeted moments, following Andrews et al. (2017). Each entry is an elasticity, $\Lambda_{kj}\hat{m}_j/\hat{\theta}_k$, where $\Lambda = (G'WG)^{-1}G'W$ and G is the Jacobian of the simulated moments with respect to the parameters, evaluated at the estimated parameters. An entry of x indicates that a one-percent increase in the empirical moment changes the parameter estimate by x percent. We estimate each element of G as the slope from a local linear regression of the simulated moment on the parameter over a window of $\pm 2.5\%$ around the estimate, which contains 25 perturbations. In each row, the bold entry identifies the moment-parameter pairing emphasized in the identification discussion of Section 5.3. The moments are: (1) mean IPO valuation multiple; (2) variance of the lead-drug stage at IPO; (3) skewness of the lead-drug stage at IPO; (4) quarterly bankruptcy hazard; (5) quarterly lead-drug failure hazard; (6) share of IPOs at Phase III or later; (7) share of firms ever reaching Phase II; and (8) quarterly lead-drug progression rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
δ	0.99	-1.45	0.44	0.50	**-0.12**	0.74	1.49	-0.66
p_0^l	0.75	-1.98	**2.30**	-1.76	-0.35	0.35	1.88	1.55
q_0	-0.72	1.69	-0.74	0.01	0.19	-0.91	**-0.26**	0.97
λ	1.19	**-1.91**	0.73	0.25	0.16	1.06	1.41	-0.73
κ	0.23	-1.20	0.90	**1.08**	0.52	0.65	2.86	0.15
γ	**1.32**	-3.39	2.62	-0.27	0.46	1.58	3.77	0.63

matrix of Andrews et al. (2017) built from it,

$$G = \left.\frac{\partial m^s(\theta)}{\partial \theta'}\right|_{\theta=\hat{\theta}}, \qquad \Lambda = \left(G'WG\right)^{-1}G'W,$$

where W is the weighting matrix in Equation (15). The element G_{jk} is the response of simulated moment j to a change in parameter k, holding the other five fixed, and Λ_{kj} is the change in $\hat{\theta}_k$ induced by a one-unit change in empirical moment j. Because the eight moments have different units, Table IA.1 reports the corresponding elasticities $\Lambda_{kj}\hat{m}_j/\hat{\theta}_k$. Online Appendix A.4 describes how we compute G.

The exercise is informative about two distinct dimensions. First, the Jacobian G demonstrates how a targeted moment responds when one parameter changes and the remaining five are held fixed. This is the object the economic argument in Section 5.3 speaks to. Second, the sensitivity matrix Λ shows how an estimate responds when one *moment* changes and the remaining seven are held fixed. It describes, as Andrews et al. (2017) show, how a small misspecification of those moments would translate into bias.

We verify the direction of each channel directly via the Jacobian matrix. At the estimated parameters, every targeted moment responds to its designated parameter with the sign the identification section discusses. The mean IPO valuation falls with γ, the variance of the stage at IPO falls with λ, skewness rises with p_0^l, the bankruptcy hazard rises with κ, the share of firms reaching Phase II rises with q_0, and the pre-IPO failure hazard falls with δ. This is the first purpose of the exercise: the model's local comparative statics should be consistent with the economic mechanisms used to motivate the targeted moments (Andrews et al., 2020).

The sensitivity matrix shows that the estimator uses all eight moments to determine each parameter, while confirming that the designated moments do the work the identification argument assigns them. Two of the six designated pairings are the largest elasticity in their row in absolute value: the skewness of the stage at IPO for p_0^l, and the variance of that distribution for λ. For the remaining four the designated moment is influential without being dominant, and the share of firms ever reaching Phase II and the variance of the stage at IPO carry weight across several rows. Four of the six designated pairings also share the sign of the corresponding direct derivative in the Jacobian. The two that do not, q_0 and γ, differ because Λ requires the inversion of $G'WG$, so a row of Λ describes how the estimator adjusts a parameter once all six are considered jointly rather than the model's direct comparative static.[10] We therefore read Λ as a description of how the estimator maps empirical moments into parameter estimates, and G as the statement of the model's economic mechanisms.

Two features of the matrix support the identification argument. First, no estimate is hostage to a single moment. The largest elasticity in Table IA.1 is 3.77, so a one-percent perturbation to any targeted moment moves any parameter estimate by at most about four percent. Because Λ is the local analogue of an omitted-variables bias formula, with asymptotic bias $\Lambda\,\Delta m$ under a perturbation Δm to the estimation moments (Andrews et al., 2017), this also bounds how far a modest misspecification of any single moment could move the estimates. Second, the estimates are correspondingly precise. The t-statistics range from 6.0 for p_0^l to 21.5 for q_0.[11] The ability gap and the low type's project prior are only mildly correlated in the sampling distribution, with a correlation of -0.27, so the decomposition of the high type's prior into $p_0^h = \delta + p_0^l$ is separately determined rather than resting on an offsetting pair of imprecise components; the implied p_0^h has a standard error of 0.042. The quantitative conclusions of Section 6.1, which turn on the size of the ability gap and on the informativeness of milestones, therefore rest on parameters that the targeted moments determine with reasonable precision.

[10] Formally, $\Lambda = (G'WG)^{-1}G'W$. When several parameters move the simulated moments in similar directions, this inversion can generate sensitivities whose signs differ from the corresponding direct derivatives in G.

[11] These t-statistics are computed from the estimates and standard errors reported in Table 8.

B Proofs

Proofs of Lemmas 1 and 2

Proof. Lemma 1. Suppose there exists a state with nondegenerate public belief $q^- \in (0,1)$, market condition α, and stage m, such that $0 < s_h < 1$ and $s_l > 0$ form a pair of equilibrium financing strategies. Let $P = \Pi_I(q^f, \alpha, m)$ denote the financing price and let $W^\theta(q^w, \alpha, m)$ denote type θ's waiting value induced by the no-financing posterior q^w.

Since the high type mixes, she must be indifferent:

$$P = W^h(q^w, \alpha, m).$$

Since the low type finances with positive probability, financing must be weakly optimal for her:

$$P \geq W^l(q^w, \alpha, m).$$

For any common no-financing belief q^w, the high type has a strictly larger waiting value than the low type,

$$W^h(q^w, \alpha, m) > W^l(q^w, \alpha, m),$$

because $p_m^h > p_m^l$, so the high type has a strictly higher probability of passing the milestone. Hence

$$P = W^h(q^w, \alpha, m) > W^l(q^w, \alpha, m).$$

Thus the low type strictly prefers financing, so sequential rationality requires $s_l = 1$. With $s_l = 1$ and $0 < s_h < 1$, observing no financing reveals the high type, so $q^w = 1$. Consider the following alternative strategy, where the high type's financing probability increases to $s_h' = 1$, keeping $s_l = 1$. The financing posterior strictly increases to

$$q^{f'} = q^- > q^f = \frac{q^- s_h}{q^- s_h + (1 - q^-)}$$

and since $\Pi_I(q, \alpha, m)$ is strictly increasing in q, the financing price strictly rises:

$$\Pi_I(q^{f'}, \alpha, m) > \Pi_I(q^f, \alpha, m) = W^h(1, \alpha, m).$$

The above equation implies that both types strictly prefer financing, consistent with their incentive constraints, with off-path no-financing belief $q^w = 1$. So the modified strategy profile is still a PBE, but it gives the high type a strictly higher value. This contradicts high-type-preferred equilibrium selection. Therefore no such equilibrium exists.

Lemma 2. We first show that $s^h > 0$ implies $s^l > 0$. Suppose, to the contrary, that there exists a state with nondegenerate public belief $q^- \in (0,1)$, market condition α, and stage m, such that $s^h > 0$ and $s^l = 0$ in equilibrium. Then financing is undertaken only by the high type, so the

financing posterior is $q^f = 1$ and the financing price is $\Pi_I(1, \alpha, m)$, which is weakly greater than the high type's waiting value.

Recall that the low type's waiting value is strictly below the high type's. By mimicking financing, the low type would obtain $\Pi_I(1, \alpha, m)$, which strictly exceeds her own waiting value. This contradicts $s^l = 0$. Therefore $s^h > 0$ implies $s^l > 0$ in equilibrium.

Now suppose $s^h = 1$, which implies $s^l > 0$ by the first part. Suppose, to the contrary, that $s^l < 1$. Then no financing occurs with positive probability and only for the low type, so Bayes' rule implies $q^w = 0$. Since financing is weakly optimal for the high type,

$$\Pi_I(q^f, \alpha, m) \geq W^h(0, \alpha, m).$$

By the same waiting-value ordering,

$$W^h(0, \alpha, m) > W^l(0, \alpha, m).$$

Therefore

$$\Pi_I(q^f, \alpha, m) > W^l(0, \alpha, m).$$

The low type strictly prefers financing, contradicting $s^l < 1$. Hence $s^l = 1$. □

Proof of Lemma 3

Proof. Fix an initial belief q at stage m. For $k \geq m$, let q_k denote the belief obtained after successive milestone passages starting from $q_m = q$, using the updating rule in Equation (6). Write

$$p_k(q_k) = q_k p_k^h + (1 - q_k) p_k^l$$

and define

$$r_k(q_k) = 1 - \lambda + \lambda p_k(q_k)$$

as the probability of passing stage k conditional on a development outcome.

We first show that the investor price Π_I is linear in α. At the terminal stage,

$$\Pi_I(q, \alpha, M) = \alpha R.$$

We guess and verify by backward induction that, for every $m < M$,

$$\Pi_I(q, \alpha, m) = A_m(q)\bar{\alpha} + B_m(q)\rho^{M-m}\alpha - C_m(q).$$

Let

$$D_m = 1 - \beta(1 - \eta_m), \qquad E_m = 1 - \rho\beta(1 - \eta_m).$$

Both are strictly positive. At stage $M-1$, the price recursion is

$$\Pi_I(q,\alpha,M-1)=\beta(1-\eta_{M-1})\mathbb{E}\Pi_I(q,\alpha_{t+1},M-1)+\beta\eta_{M-1}r_{M-1}(q)\mathbb{E}[\alpha_{t+1}R]-\gamma R.$$

Using $\mathbb{E}[\alpha_{t+1}\mid\alpha_t=\alpha]=\bar{\alpha}+\rho\alpha$, solving this linear equation gives

$$\Pi_I(q,\alpha,M-1) \;=\; \frac{\beta\eta_{M-1}r_{M-1}(q)}{D_{M-1}E_{M-1}}R\bar{\alpha}+\frac{\beta\eta_{M-1}r_{M-1}(q)}{E_{M-1}}R\rho\alpha-\frac{\gamma R}{D_{M-1}}.$$

Thus the affine form holds one stage before terminal.

Now suppose the affine form holds at stage $m+1$. At stage m, write

$$\Pi_I(q,\alpha,m)=A_m(q)\bar{\alpha}+B_m(q)\rho^{M-m}\alpha-C_m(q).$$

Then

$$\mathbb{E}\Pi_I(q,\alpha_{t+1},m)=\big[A_m(q)+B_m(q)\rho^{M-m}\big]\bar{\alpha}+B_m(q)\rho^{M-m+1}\alpha-C_m(q),$$

and

$$\mathbb{E}\Pi_I(q_{m+1},\alpha_{t+1},m{+}1)=\big[A_{m+1}(q_{m+1}){+}B_{m+1}(q_{m+1})\rho^{M-m-1}\big]\bar{\alpha}{+}B_{m+1}(q_{m+1})\rho^{M-m}\alpha{-}C_{m+1}(q_{m+1}).$$

Substituting these expressions into Equation (9) and matching the coefficients of $\bar{\alpha}$, α, and the constant gives

$$\begin{aligned}
D_mA_m(q) &= \beta(1-\eta_m)B_m(q)\rho^{M-m}+\beta\eta_m r_m(q)\big[A_{m+1}(q_{m+1})+B_{m+1}(q_{m+1})\rho^{M-m-1}\big],\\
E_mB_m(q) &= \beta\eta_m r_m(q)B_{m+1}(q_{m+1}),\\
D_mC_m(q) &= \beta\eta_m r_m(q)C_{m+1}(q_{m+1})+\gamma R.
\end{aligned}$$

Starting from $A_M(q)=0$, $B_M(q)=R$, and $C_M(q)=0$, iterating these recursions yields

$$A_m(q) \;=\; \Big(\textstyle\prod_{j=m}^{M-1}\beta\eta_j r_j(q_j)\Big)\Big(\sum_{k=m}^{M-1}\rho^{M-1-k}\prod_{\ell=m}^{k}\frac{1}{D_\ell}\prod_{\ell=k}^{M-1}\frac{1}{E_\ell}\Big)R, \tag{20}$$

$$B_m(q) \;=\; \Big(\textstyle\prod_{k=m}^{M-1}\frac{\beta\eta_k r_k(q_k)}{E_k}\Big)R, \tag{21}$$

$$C_m(q) \;=\; \Big(\textstyle\sum_{k=m}^{M-1}\frac{1}{D_k}\prod_{\ell=m}^{k-1}\frac{\beta\eta_\ell r_\ell(q_\ell)}{D_\ell}\Big)\gamma R, \tag{22}$$

where an empty product equals one. Therefore

$$\Pi_I(q,\alpha,m)=A_m(q)\bar{\alpha}+B_m(q)\rho^{M-m}\alpha-C_m(q).$$

Because $A_m(q)$, $B_m(q)$, and $C_m(q)$ are all proportional to R, the normalized price

$$\pi_I(q,\alpha,m)=\Pi_I(q,\alpha,m)/R$$

is independent of R. Since $r_k(q_k) > 0$, we have $a_m(q), b_m(q) > 0$ and $c_m(q) \geq 0$. Moreover, $a_m(q)$ and $b_m(q)$ are strictly increasing in q, because the milestone-passage update preserves the ordering of beliefs, each q_k is increasing in the initial belief q, and $p_k(q_k)$ is increasing in q_k. This proves the affine form and price homogeneity.

Value homogeneity and financing strategies. We next show that the entrepreneur's value is homogeneous of degree one in R. At the terminal stage,

$$V^\theta(q^-, \alpha, M) = \alpha R,$$

so the claim holds. Fix a Markov financing strategy profile and the posteriors it induces. These posteriors are determined by Bayes' rule and do not involve R. Suppose the continuation value at stage $m+1$ is homogeneous of degree one in R. At stage m, financing pays

$$\Pi_I(q^f, \alpha, m) = R\,\pi_I(q^f, \alpha, m),$$

by the price homogeneity shown above.

To handle waiting, consider the stage-m Bellman operator for type θ. For a candidate same-stage value function U, define

$$\mathcal{T}_R U(q^-, \alpha) = \max\Bigg\{ R\,\pi_I(q^f, \alpha, m),$$
$$(1-\kappa)\Big[\beta(1-\eta_m)\mathbb{E}U(q^w, \alpha_{t+1}) + \beta\eta_m\big(1-\lambda(1-p_m^\theta)\big)\mathbb{E}V^\theta(q_+^w, \alpha_{t+1}, m+1)\Big] - \gamma R\Bigg\}.$$

The only term involving the candidate same-stage value U is the no-result continuation term, whose coefficient is $(1-\kappa)\beta(1-\eta_m) < 1$. Hence $\mathcal{T}_R$ is a contraction. By the induction hypothesis,

$$V^\theta(q_+^w, \alpha_{t+1}, m+1) = R\,v^\theta(q_+^w, \alpha_{t+1}, m+1).$$

Therefore, for any normalized candidate value u,

$$\mathcal{T}_R(Ru) = R\,\mathcal{T}_1 u.$$

since the fixed point of a contraction is unique. Thus

$$V^\theta(q^-, \alpha, m) = R\,v^\theta(q^-, \alpha, m),$$

with v^θ independent of R. The associated waiting value also satisfies

$$W^\theta(q^-, \alpha, m) = R\,w^\theta(q^-, \alpha, m).$$

Finally, since $R > 0$, the financing decision compares

$$R\,\pi_I(q^f, \alpha, m) \quad \text{with} \quad R\,w^\theta(q^-, \alpha, m),$$

or equivalently compares

$$\pi_I(q^f, \alpha, m) \quad \text{with} \quad w^\theta(q^-, \alpha, m).$$

This comparison does not involve R. Therefore the best-response correspondence, equilibrium financing strategies, and any equilibrium mixing probabilities are independent of R. The high-type-preferred selection is also unchanged, because multiplying all high-type payoffs by the positive scalar R does not change their ranking across equilibria. This completes the proof of Lemma 3. □

Proof of Proposition 1

Proof. The proof uses two auxiliary results. Lemma 4 shows that, once the entrepreneur's type is known, immediate financing is optimal; hence $v^h(1, \alpha, m) = \pi_I(1, \alpha, m)$ and $v^l(0, \alpha, m) = \pi_I(0, \alpha, m)$. This result lets us evaluate continuation values when a financing or no-financing decision reveals the entrepreneur's type. The statement of Lemma 4 is in the main text. Lemma 5 records coefficient recursions implied by the affine price formula in Lemma 3. These identities are used to sign the high type's financing surplus and derive her cutoff. We prove the two auxiliary results first and then complete the cutoff construction.

Lemma 5. *For every $m < M$ and belief q,*

$$\begin{aligned}
A_m(q) &= \beta(1-\eta_m)\big(A_m(q) + B_m(q)\rho^{M-m}\big) \\
&\quad +\beta\eta_m\big(1-\lambda(1-p_m(q))\big)\big(A_{m+1}(q_{m+1}) + B_{m+1}(q_{m+1})\rho^{M-m-1}\big), \\
B_m(q) &= \beta(1-\eta_m)B_m(q)\rho + \beta\eta_m\big(1-\lambda(1-p_m(q))\big)B_{m+1}(q_{m+1}), \\
C_m(q) &= \beta(1-\eta_m)C_m(q) + \beta\eta_m\big(1-\lambda(1-p_m(q))\big)C_{m+1}(q_{m+1}) + \gamma R.
\end{aligned}$$

Proof of Lemma 4

Fix a type $\theta \in \{h, l\}$, and let $\bar{q}^\theta$ denote the belief that reveals the type: $\bar{q}^h = 1$ and $\bar{q}^l = 0$. Write

$$P_m^\theta(\alpha) \equiv \Pi_I(\bar{q}^\theta, \alpha, m), \qquad U_m^\theta(\alpha) \equiv V^\theta(\bar{q}^\theta, \alpha, m),$$

and let $r_m^\theta \equiv 1 - \lambda(1 - p_m^\theta)$. We prove by backward induction on m that $U_m^\theta(\alpha) = P_m^\theta(\alpha)$ at every active state. At $m = M$, both values equal αR, so the claim holds.

Suppose the claim holds at stage $m+1$. Since financing is always feasible at stage m, we have $U_m^\theta(\alpha) \geq P_m^\theta(\alpha)$. Define

$$\Delta_m^\theta(\alpha) \equiv U_m^\theta(\alpha) - P_m^\theta(\alpha) \geq 0.$$

If the entrepreneur waits, the type remains known, so by the induction hypothesis the passed-

milestone continuation value is P^{θ}_{m+1}. Thus

$$W^{\theta}_m(\alpha) = (1-\kappa)\left[\beta(1-\eta_m)\mathbb{E}U^{\theta}_m(\alpha_{t+1}) + \beta\eta_m r^{\theta}_m \mathbb{E}P^{\theta}_{m+1}(\alpha_{t+1})\right] - \gamma R.$$

The zero-profit price satisfies

$$P^{\theta}_m(\alpha) = \beta(1-\eta_m)\mathbb{E}P^{\theta}_m(\alpha_{t+1}) + \beta\eta_m r^{\theta}_m \mathbb{E}P^{\theta}_{m+1}(\alpha_{t+1}) - \gamma R.$$

Subtracting the two equations gives

$$W^{\theta}_m(\alpha) - P^{\theta}_m(\alpha) = (1-\kappa)\beta(1-\eta_m)\mathbb{E}\Delta^{\theta}_m(\alpha_{t+1}) - \kappa\left[\beta(1-\eta_m)\mathbb{E}P^{\theta}_m(\alpha_{t+1}) + \beta\eta_m r^{\theta}_m \mathbb{E}P^{\theta}_{m+1}(\alpha_{t+1})\right].$$

At active states the revealed-type continuation prices are nonnegative, so

$$W^{\theta}_m(\alpha) - P^{\theta}_m(\alpha) \leq (1-\kappa)\beta(1-\eta_m)\mathbb{E}\Delta^{\theta}_m(\alpha_{t+1}).$$

Since $U^{\theta}_m(\alpha) = \max\{P^{\theta}_m(\alpha), W^{\theta}_m(\alpha)\}$,

$$\Delta^{\theta}_m(\alpha) \leq (1-\kappa)\beta(1-\eta_m)\mathbb{E}\Delta^{\theta}_m(\alpha_{t+1}).$$

The coefficient $(1-\kappa)\beta(1-\eta_m)$ is strictly less than one. Hence the only nonnegative fixed point is $\Delta^{\theta}_m \equiv 0$. Therefore $U^{\theta}_m(\alpha) = P^{\theta}_m(\alpha)$, so immediate financing is optimal at stage m. By backward induction, immediate financing is optimal at every active state. Thus

$$V^h(1,\alpha,m) = \Pi_I(1,\alpha,m), \qquad V^l(0,\alpha,m) = \Pi_I(0,\alpha,m).$$

Dividing by R gives

$$v^h(1,\alpha,m) = \pi_I(1,\alpha,m), \qquad v^l(0,\alpha,m) = \pi_I(0,\alpha,m).$$

□

Proof of Lemma 5

Substitute $\Pi_I(q,\alpha,m) = A_m(q)\bar{\alpha} + B_m(q)\rho^{M-m}\alpha - C_m(q)$ into the right-hand side of Equation (9). Using

$$\mathbb{E}\,\Pi_I(q,\alpha_{t+1},m) = \left(A_m(q) + B_m(q)\rho^{M-m}\right)\bar{\alpha} + B_m(q)\rho^{M-m+1}\alpha - C_m(q),$$

and the analogous expression at $(q_{m+1}, m+1)$, matching the coefficients of $\bar{\alpha}$, α, and the constant term yields the three displayed equations. Both continuation prices are evaluated at their *own* stages, m and $m+1$. □

The proof proceeds in seven steps. Step 1 uses Lemmas 1 and 2 to restrict the possible local strategy profiles. Step 2 derives the high-type cutoff $\alpha^*_h(q^-,m)$, including the case in which the high

type never finances. Step 3 derives the low-type cutoff $\alpha_l^*(q^-, m)$ and establishes uniqueness under the slope condition $\kappa \geq \bar{\kappa}$. Step 4 constructs the low-type mixing probability in the semi-pooling region. Step 5 verifies the incentive constraints. Step 6 verifies belief consistency and investor break-even. Step 7 applies the high-type-preferred equilibrium selection.

Step 1. Fix a nondegenerate public belief $q^- \in (0,1)$ and stage $m < M$. By Lemma 2, $s^h > 0$ implies $s^l > 0$. Given $s^l > 0$, Lemma 1 rules out interior high-type mixing in the high-type-preferred equilibrium. Hence, if the high type finances with positive probability, she must finance with probability one. Lemma 2 then implies $s^l = 1$. Therefore any state with $s^h > 0$ must have

$$(s^h, s^l) = (1, 1).$$

If instead $s^h = 0$, either the low type also waits, giving $(s^h, s^l) = (0, 0)$, or the low type finances with positive probability, giving $(s^h, s^l) = (0, s^l)$ with $s^l > 0$. Thus the only local strategy profiles that can arise in the high-type-preferred equilibrium are

$$(s^h, s^l) \in \{(0,0), (1,1), (0, s^l) \text{ with } s^l > 0\}.$$

It remains to construct the valuation regions in which these three configurations apply.

Step 2. Fix $q^- \in (0,1)$ and $m < M$. Consider a state in which the high type finances. By Step 1, both types finance, so the financing posterior is $q^f = q^-$. If the high type deviates to waiting, off-equilibrium belief reveals the high type and hence $q^w = 1$. By Lemma 4, $v^h(1, \alpha, m) = \pi_I(1, \alpha, m)$. Therefore the high type's waiting payoff after such a deviation is

$$\begin{aligned}
\widehat{W}^h(\alpha, m) &= (1-\kappa)\Big[\beta(1-\eta_m)\mathbb{E}\pi_I(1, \alpha_{t+1}, m) + \beta\eta_m\big(1-\lambda(1-p_m^h)\big)\mathbb{E}\pi_I(1, \alpha_{t+1}, m+1)\Big] - \gamma \\
&= (1-\kappa)\big(\pi_I(1, \alpha, m) + \gamma\big) - \gamma \\
&= (1-\kappa)\pi_I(1, \alpha, m) - \kappa\gamma,
\end{aligned}$$

where the second equality uses the normalized zero-profit pricing equation at belief $q = 1$. Thus the high type finances iff

$$G_h(q^-, \alpha, m) \equiv \pi_I(q^-, \alpha, m) - (1-\kappa)\pi_I(1, \alpha, m) + \kappa\gamma \geq 0.$$

Using the affine price formula in Lemma 3,

$$G_h(q^-, \alpha, m) = \big(a_m(q^-) - (1-\kappa)a_m(1)\big)\bar{\alpha} + \big(b_m(q^-) - (1-\kappa)b_m(1)\big)\rho^{M-m}\alpha - c_m(q^-) + (1-\kappa)c_m(1) + \kappa\gamma.$$

Let

$$\Lambda_m(q^-) \equiv \frac{a_m(q^-)}{a_m(1)} = \frac{b_m(q^-)}{b_m(1)}.$$

By Lemma 3, $\Lambda_m(q^-)$ is strictly increasing in q^- and $\Lambda_m(1) = 1$. Hence the slope of G_h in α has the sign of $\Lambda_m(q^-) - (1-\kappa)$. Define $\widetilde{q}(m)$ by $\Lambda_m(\widetilde{q}(m)) = 1 - \kappa$, with the natural boundary

convention if the solution lies outside $(0,1)$.

If $q^- > \widetilde{q}(m)$, then $G_h(q^-, \alpha, m)$ is strictly increasing in α. Hence there is a unique upper-threshold rule. Let $\underline{\alpha}$ denote the lower bound of the valuation support. The cutoff is

$$\alpha_h^*(q^-, m) = \max\left\{\underline{\alpha},\ \frac{\big((1-\kappa)a_m(1) - a_m(q^-)\big)\bar{\alpha} + c_m(q^-) - (1-\kappa)c_m(1) - \kappa\gamma}{\big(b_m(q^-) - (1-\kappa)b_m(1)\big)\rho^{M-m}}\right\}.$$

The high type finances iff $\alpha \geq \alpha_h^*(q^-, m)$.

If $q^- \leq \widetilde{q}(m)$, then $G_h(q^-, \alpha, m)$ is weakly decreasing in α. Under the never-finance condition

$$G_h(q^-, \underline{\alpha}, m) \leq 0,$$

the high-type surplus is nonpositive throughout the valuation support, so the high type never finances. We set $\alpha_h^*(q^-, m) = +\infty$.

Step 3. Consider states below the high-type cutoff, $\alpha < \alpha_h^*(q^-, m)$, where the high type waits. If the low type finances in this region, financing reveals her type, so $q^f = 0$ and her financing payoff is $\pi_I(0, \alpha, m)$. At the lower boundary of the low-type financing region, the low type's financing probability tends to zero, so the no-financing posterior remains q^-. Define the corresponding low-type waiting payoff by

$$\widehat{W}^l(q^-, \alpha, m) = (1-\kappa)\left[\beta(1-\eta_m)\mathbb{E}v^l(q^-, \alpha_{t+1}, m) + \beta\eta_m\big(1 - \lambda(1-p_m^l)\big)\mathbb{E}v^l(q_+^-, \alpha_{t+1}, m+1)\right] - \gamma,$$

where q_+^- is the milestone-updated belief obtained from Equation (6) starting from q^-. Define the low-type financing surplus

$$G_l(q^-, \alpha, m) \equiv \pi_I(0, \alpha, m) - \widehat{W}^l(q^-, \alpha, m).$$

A positive value of G_l means that the low type prefers revealing financing to waiting.

We now impose the slope condition. Choose $\bar{\kappa} \in (0,1)$ such that, for all $\kappa \geq \bar{\kappa}$ and all $\alpha < \alpha_h^*(q^-, m)$,

$$\frac{\partial \widehat{W}^l(q^-, \alpha, m)}{\partial \alpha} < \frac{\partial \pi_I(0, \alpha, m)}{\partial \alpha} = b_m(0)\rho^{M-m}.$$

Such a $\bar{\kappa}$ exists because the derivative of the waiting payoff is multiplied by the survival factor $1-\kappa$, so it converges uniformly to zero as $\kappa \to 1$, while $b_m(0)\rho^{M-m} > 0$ is independent of κ. Hence $G_l(q^-, \alpha, m)$ is continuous and strictly increasing in α.

Let $\underline{\alpha}$ denote the lower bound of the valuation support. If

$$G_l(q^-, \underline{\alpha}, m) \geq 0,$$

then revealing financing is already weakly optimal for the low type at the lowest valuation, and we

set

$$\alpha_l^*(q^-, m) = \underline{\alpha}.$$

If instead $G_l(q^-, \underline{\alpha}, m) < 0$, then the low type strictly prefers waiting at $\underline{\alpha}$. As $\alpha \to \infty$, the affine financing payoff $\pi_I(0, \alpha, m)$ grows with slope $b_m(0)\rho^{M-m} > 0$, while the slope condition keeps the waiting payoff flatter. Therefore

$$G_l(q^-, \alpha, m) \to \infty.$$

By continuity, there exists a crossing, and because G_l is strictly increasing, the crossing is unique. Thus there is a unique cutoff $\alpha_l^*(q^-, m)$ satisfying

$$\pi_I(0, \alpha_l^*, m) = \widehat{W}^l(q^-, \alpha_l^*, m),$$

whenever the cutoff is interior, with the boundary convention $\alpha_l^*(q^-, m) = \underline{\alpha}$ when financing is already optimal at the lower bound. The cutoff is independent of R by Lemma 3.

Step 4. If $\alpha_l^*(q^-, m) \geq \alpha_h^*(q^-, m)$, the semi-pooling region is empty, and the low type finances only in the pool-financing region where the high type also finances. Now suppose $\alpha_l^*(q^-, m) < \alpha_h^*(q^-, m)$. For any $\alpha \in [\alpha_l^*(q^-, m), \alpha_h^*(q^-, m))$, the high type waits and the low type finances with probability $p \in [0, 1]$. The no-financing posterior is

$$Q^*(p) = \frac{q^-}{q^- + (1 - q^-)(1 - p)}.$$

This posterior is continuous and strictly increasing in p, with $Q^*(0) = q^-$ and $Q^*(1) = 1$.

For a given posterior Q, let

$$\widehat{W}^l(Q, \alpha, m) = (1 - \kappa)\left[\beta(1 - \eta_m)\mathbb{E}v^l(Q, \alpha_{t+1}, m) + \beta\eta_m\big(1 - \lambda(1 - p_m^l)\big)\mathbb{E}v^l(Q_+, \alpha_{t+1}, m + 1)\right] - \gamma$$

denote the low type's waiting payoff when the no-financing posterior is Q, where Q_+ is the milestone-updated belief starting from Q. The mixing probability is chosen to satisfy

$$\pi_I(0, \alpha, m) = \widehat{W}^l(Q^*(p), \alpha, m).$$

Define

$$\Phi(p) \equiv \widehat{W}^l(Q^*(p), \alpha, m) - \pi_I(0, \alpha, m).$$

The function Φ is continuous in p. It is also weakly increasing because a higher no-financing posterior raises the continuation value of waiting.

At $p = 0$, $Q^*(0) = q^-$, so

$$\Phi(0) = \widehat{W}^l(q^-, \alpha, m) - \pi_I(0, \alpha, m) \leq 0$$

for $\alpha \geq \alpha_l^*(q^-, m)$ by the definition of the low-type cutoff. At $p = 1$, $Q^*(1) = 1$. If

$$\Phi(1) \geq 0,$$

then by continuity there exists $p(\alpha, q^-, m) \in [0, 1]$ such that $\Phi(p) = 0$. At any interior solution, the low type is indifferent between financing and waiting. If instead $\Phi(1) < 0$, then even the most favorable no-financing posterior does not make waiting attractive enough, and the low type strictly prefers financing for every $p < 1$. In that case set

$$p(\alpha, q^-, m) = 1.$$

Thus the low-type financing probability is well defined throughout the semi-pooling region.

When Φ is strictly increasing, the interior mixing probability is unique. Strict monotonicity follows whenever a higher no-financing posterior strictly raises the low type's continuation value, which holds because higher beliefs raise future financing prices by Lemma 3. Therefore the semi-pooling posterior and mixing probability are unique whenever the solution is interior.

Step 5. We now verify incentive compatibility for the candidate strategy profile. First consider the high type. By construction, she finances for $\alpha \geq \alpha_h^*(q^-, m)$ and waits for $\alpha < \alpha_h^*(q^-, m)$. Her financing surplus at the pooled financing belief is

$$G_h(q^-, \alpha, m) = \pi_I(q^-, \alpha, m) - (1 - \kappa)\pi_I(1, \alpha, m) + \kappa\gamma.$$

From Step 2, $G_h(q^-, \alpha, m) \geq 0$ exactly in the region where the high type finances, and $G_h(q^-, \alpha, m) < 0$ in the region where she waits. Therefore financing is optimal in the pool-financing region. For $\alpha < \alpha_h^*(q^-, m)$, the high type does not want to finance even at the pooled belief q^-:

$$\pi_I(q^-, \alpha, m) < (1 - \kappa)\pi_I(1, \alpha, m) - \kappa\gamma.$$

In the pool-wait region, financing is off path because both types wait, and the imposed off-path belief is $q^f = 0$. Since $\pi_I(0, \alpha, m) \leq \pi_I(q^-, \alpha, m)$, an off-path financing deviation is even less attractive. In the semi-pooling region, financing is on path only for the low type, so a high-type deviation to financing is again priced at $q^f = 0$. Hence the high type has no profitable deviation.

Next consider the low type. If $\alpha < \alpha_l^*(q^-, m)$, then by Step 3,

$$\pi_I(0, \alpha, m) \leq \widehat{W}^l(q^-, \alpha, m),$$

so the low type weakly prefers waiting to revealing financing. Hence she has no profitable financing deviation in the pool-wait region. If $\alpha_l^*(q^-, m) \leq \alpha < \alpha_h^*(q^-, m)$, the low type mixes. Step 4 chooses $p(\alpha, q^-, m)$ so that

$$\pi_I(0, \alpha, m) = \widehat{W}^l(Q^*(p), \alpha, m),$$

so the low type is indifferent between financing and waiting and randomization is optimal.

Finally, if $\alpha \geq \alpha_h^*(q^-, m)$, both types finance. Since financing is weakly optimal for the high type at these states, Lemma 2 implies that the low type strictly prefers financing whenever the high type finances with probability one. Therefore the low type has no profitable deviation to waiting in the pool-financing region. This verifies both types' incentive constraints.

Step 6. We next verify belief consistency and investor break-even. On the equilibrium path, beliefs are updated by Bayes' rule. In the pool-wait region, both types wait, so no financing leaves the belief unchanged at $q^w = q^-$. If a milestone is passed after waiting, the belief updates to q_+^w according to Equation (6). Financing is off path in this region, and the imposed off-path belief is $q^f = 0$ following the D1 criterion.

In the semi-pooling region, the high type waits and the low type finances with probability $p(\alpha, q^-, m)$. Conditional on financing, Bayes' rule gives $q^f = 0$. Conditional on no financing, Bayes' rule gives

$$q^w = Q^*(p) = \frac{q^-}{q^- + (1 - q^-)(1 - p)}.$$

After a passed milestone, the belief updates from $Q^*(p)$ to $Q_+^*(p)$ according to Equation (6).

In the pool-financing region, both types finance, so financing leaves the belief unchanged at $q^f = q^-$. No financing is off path in this region. We assign the off-path no-financing belief $q^w = 1$, consistent with the high-type waiting deviation used to define $\alpha_h^*(q^-, m)$.

Finally, for every posterior belief q, the financing price $\pi_I(q, \alpha, m)$ satisfies the normalized zero-profit recursion,

$$\pi_I(q, \alpha, m) = \beta(1 - \eta_m)\mathbb{E}\pi_I(q, \alpha_{t+1}, m) + \beta\eta_m\big(1 - \lambda(1 - p_m(q))\big)\mathbb{E}\pi_I(q_+, \alpha_{t+1}, m + 1) - \gamma.$$

Thus investors break even at every financing posterior. Therefore the candidate strategies, beliefs, and prices satisfy the consistency and investor optimality requirements of an MPBE

Step 7. The constructed equilibrium is high-type preferred. By Step 1, any high-type-preferred MPBE can use only the three local configurations: pool-wait, pool-financing, or semi-pooling with $s^h = 0$ and $s^l > 0$. Step 2 shows that the high type's financing surplus $G_h(q^-, \alpha, m)$ is monotone in α and crosses zero at $\alpha_h^*(q^-, m)$, when a finite crossing exists. Hence any non-cutoff high-type strategy would either make her finance at a state where $G_h < 0$ or wait at a state where $G_h > 0$, violating her incentive constraint. Step 3 gives the analogous single-crossing condition for the low type's revealing-financing surplus below α_h^*, so the boundary of the low-type financing region is $\alpha_l^*(q^-, m)$. Step 4 then selects a mixing probability in the semi-pooling region that makes the low type indifferent.

Thus no non-cutoff arrangement can satisfy sequential rationality while giving the high type a higher value. Lemma 1 also rules out improving the high type by introducing interior high-type mixing when the low type finances with positive probability. Therefore the constructed PBE is the high-type-preferred MPBE. The cutoffs and financing strategies are independent of R by Lemma 3. This completes the proof of Proposition 1. □

Proof of Proposition 2

Proof. Fix a type $\theta \in \{h, l\}$, with revealing belief $\bar{q}^\theta \in \{0, 1\}$. By homogeneity (Lemma 3), we work throughout with the normalized value v^θ, price π_I, and flow cost γ; the recursions Equation (7), Equation (8), and Equation (9) hold verbatim with $R = 1$. Let $s^\theta \equiv s^\theta(q^-, \alpha, m)$ be the equilibrium financing probability, let q^f be the induced financing posterior, and define the total value gap

$$\Delta^\theta(\alpha, q^-, m) \equiv \pi_I(\bar{q}^\theta, \alpha, m) - v^\theta(q^-, \alpha, m).$$

For any function g of $(\text{belief}, \alpha, m)$, write $\mathbb{C}^\theta g$ for the one-step development continuation along the no-financing path, excluding discounting and the liquidity-survival factor:

$$\mathbb{C}^\theta g \equiv (1 - \eta_m)\mathbb{E}g(q^w, \alpha_{t+1}, m) + \eta_m\big(1 - \lambda(1 - p_m^\theta)\big)\mathbb{E}g(q_+^w, \alpha_{t+1}, m + 1),$$

where a failed milestone ends the game and contributes zero. The proof proceeds in three steps. Step 1 derives recursive equations for the mispricing and liquidation components. Step 2 shows that the total value gap satisfies the sum of those two recursions. Step 3 uses the common terminal condition and contraction to conclude equality.

Step 1. At the absorbing belief $\bar{q}^\theta$, where $q^w = q_+^w = \bar{q}^\theta$ and $p_m(\bar{q}^\theta) = p_m^\theta$, the normalized price recursion Equation (9) reads

$$\pi_I(\bar{q}^\theta, \alpha, m) = \beta\, \mathbb{C}^\theta \pi_I(\bar{q}^\theta, \cdot) - \gamma.$$

Equivalently,

$$\beta\, \mathbb{C}^\theta \pi_I(\bar{q}^\theta, \cdot) = \pi_I(\bar{q}^\theta, \alpha, m) + \gamma. \tag{23}$$

Condition the definitions Equation (16)–Equation (17) on the current period. Type θ finances with probability s^θ at posterior q^f. If she does not finance, she pays γ, survives the liquidity shock with probability $1 - \kappa$, and is liquidated with probability κ. The law of iterated expectations gives, for $m < M$,

$$\begin{aligned} mp^\theta(\alpha, q^-, m) &= s^\theta\big(\pi_I(\bar{q}^\theta, \alpha, m) - \pi_I(q^f, \alpha, m)\big) + (1 - s^\theta)(1 - \kappa)\beta\, \mathbb{C}^\theta mp^\theta, & (24)\\ liq^\theta(\alpha, q^-, m) &= (1 - s^\theta)\Big(\kappa\big(\pi_I(\bar{q}^\theta, \alpha, m) + \gamma\big) + (1 - \kappa)\beta\, \mathbb{C}^\theta liq^\theta\Big), & (25) \end{aligned}$$

with terminal values $mp^\theta(\cdot, \cdot, M) = liq^\theta(\cdot, \cdot, M) = 0$. The per-period liquidation loss in Equation (25) is $\kappa(\pi_I(\bar{q}^\theta, \alpha, m) + \gamma)$: the shock destroys the project's first-best continuation value after the current flow cost has been paid; by Equation (23), this value is $\pi_I(\bar{q}^\theta, \alpha, m) + \gamma$.

Step 2. Since the entrepreneur finances with probability s^θ and waits otherwise, Equation (7)–Equation (8) give

$$v^\theta(q^-, \alpha, m) = s^\theta \pi_I(q^f, \alpha, m) + (1 - s^\theta)\big((1 - \kappa)\beta\, \mathbb{C}^\theta v^\theta - \gamma\big).$$

Subtracting this from $\pi_I(\bar{q}^\theta, \alpha, m) = s^\theta \pi_I(\bar{q}^\theta, \alpha, m) + (1 - s^\theta)\pi_I(\bar{q}^\theta, \alpha, m)$ and applying Equation (23)

on the no-financing branch,

$$\begin{aligned}\Delta^\theta(\alpha, q^-, m) &= s^\theta\big(\pi_I(\bar{q}^\theta, \alpha, m) - \pi_I(q^f, \alpha, m)\big) + (1 - s^\theta)\big(\pi_I(\bar{q}^\theta, \alpha, m) + \gamma - (1-\kappa)\beta\,\mathbb{C}^\theta v^\theta\big) \\ &= s^\theta\big(\pi_I(\bar{q}^\theta, \alpha, m) - \pi_I(q^f, \alpha, m)\big) + (1 - s^\theta)\big(\beta\,\mathbb{C}^\theta \pi_I(\bar{q}^\theta, \cdot) - (1-\kappa)\beta\,\mathbb{C}^\theta v^\theta\big) \\ &= s^\theta\big(\pi_I(\bar{q}^\theta, \alpha, m) - \pi_I(q^f, \alpha, m)\big) + (1 - s^\theta)\Big(\kappa\big(\pi_I(\bar{q}^\theta, \alpha, m) + \gamma\big) + (1-\kappa)\beta\,\mathbb{C}^\theta \Delta^\theta\Big),\end{aligned}$$

where the last line uses

$$\mathbb{C}^\theta \pi_I(\bar{q}^\theta, \cdot) - \mathbb{C}^\theta v^\theta = \mathbb{C}^\theta \Delta^\theta$$

together with Equation (23). This is precisely the sum of Equation (24) and Equation (25), with Δ^θ in the role of $mp^\theta + liq^\theta$.

Step 3. At the terminal stage, $\pi_I(\bar{q}^\theta, \alpha, M) = v^\theta(q^-, \alpha, M) = \alpha$, so

$$\Delta^\theta(\cdot, \cdot, M) = 0 = mp^\theta(\cdot, \cdot, M) + liq^\theta(\cdot, \cdot, M).$$

Thus Δ^θ and $mp^\theta + liq^\theta$ satisfy the same recursion with the same terminal condition. We solve backward in m. At a given stage m, taking the stage-$(m+1)$ functions as given, the same-stage continuation enters only through the no-development-outcome term and has coefficient $(1-\kappa)\beta(1-\eta_m) < 1$. Hence the stage-$m$ recursion is a contraction and has a unique fixed point. Since both Δ^θ and $mp^\theta + liq^\theta$ solve this same fixed-point problem, they must be equal:

$$\Delta^\theta(\alpha, q^-, m) = mp^\theta(\alpha, q^-, m) + liq^\theta(\alpha, q^-, m)$$

at every active state. This is Equation (18). □