Debt as Information Shield: Evidence from Pharmaceutical Startups

March 31, 2026

Abstract

This paper examines the role of proprietary information in determining startup capital structure. I exploit the 2014 FDA Final Rule, which mandates public disclosure of clinical trial results, as an exogenous shock to the proprietary information environment of pharmaceutical startups. I find that this mandatory disclosure shock is associated with 1.5 percentage point decline in venture debt usage, representing a 36% drop from the pre-shock mean. This flight from debt is driven by the proprietary costs of disclosure: a one-standard-deviation increase in competitor technology similarity amplifies the drop by 1.8 percentage points. Within these competitive markets, startups developing novel drugs drive this shift away from debt. These findings indicate that the information sensitivity of a financial instrument and the competitive structure of the product market jointly determine the startup capital structure, extending the classic "disclosure-financing trade-off" to the choice of financial instrument.

1 Introduction

Startups are often recognized as facing high information asymmetry and must actively disclose their proprietary information to get better financing terms (Gompers 2002; Berger and Udell, 1998; Kaplan and Strömberg, 2003; Kerr and Nanda, 2011). At the same time, startups also face a fierce competition environment, which means that the disclosed information may be exploited by competitors to the disclosing firm's disadvantage. (Audretsch and Mahmood, 1995; Kamepalli et al., 2020). For example, rivals might free-ride on disclosed data to accelerate their own competing products. Verrecchia (1983) defines this leakage of proprietary information as "proprietary cost of disclosure" and highlights that the disclosure threshold is the point at which expected proprietary costs of disclosure equal the benefits of reduced information asymmetry.

Bhattacharya and Ritter (1983) formalized that when disclosure has two audiences: outside financiers and product-market competitors, firms face a fundamental tradeoff between enduring adverse selection in financial markets and revealing proprietary information to rivals. Subsequent empirical research has explored this tradeoff along two dimensions. One strand of empirical literature studies how proprietary costs shape the volume and format of disclosure (Boone et al., 2016; Baruffaldi et al., 2024; Kankanhalli et al., 2024; Kim and Valentine, 2021; Ali et al., 2014; Ellis et al., 2012). A second strand of literature studies the choice of the financier as information receiver (Asker and Ljungqvist, 2010; Bae et al., 2024; Bhattacharya and Chiesa, 1995; Floros et al., 2024; Yosha, 1995).

However, both strands largely ignored that different financial instruments require fundamentally different levels of information disclosure at origination. Dang et al. (2012) show that debt is less information sensitive than equity: creditors hold a fixed claim and need only verify solvency, whereas equity investors must evaluate the full distribution of upside outcomes. This implies that a debt lender extracts far less proprietary information than an equity investor, who requires extensive due diligence, syndication discussions, and board-level oversight at origination. The information cost embedded in the financing instrument

can therefore be a key factor in capital structure choice: firms may have the incentive to choose debt as an "information shield" because it discloses less proprietary information to the competitive environment. Hereafter, I refer to it as the "debt as information shield" hypothesis.

This information-sensitivity difference has a clear implication for capital structure: firms holding highly valuable proprietary information should prefer financial instruments that extract less of it. How large this secrecy benefit is depends on three factors: how many rivals surround the firm, how well those rivals can absorb disclosed information, and how novel the disclosed information is. A crowded market alone does not make disclosure costly — what matters is whether the rivals have the ability to possess the technological capacity to translate disclosed information into competing product progress, and whether the disclosed information advances the frontier beyond what rivals already know. The demand for information-insensitive instruments should therefore be jointly determined by competitive structure and information novelty. Furthermore, this logic implies a hierarchy even within debt instruments: instruments requiring equity-like upside assessment at origination—such as convertible debt—should provide a weaker shield than pure venture debt.

Empirically testing this mechanism requires distinguishing between product market competition and information leakage, a nuance that previous literature often overlooks. As Bloom, Schankerman, and Van Reenen (2013) demonstrate, using competitive threat as a proxy for the proprietary cost of disclosure is flawed because it confounds product market competition with technology spillover effects. Despite this, existing literature establishing that firms in competitive markets disclose less typically assumes that crowded markets automatically guarantee higher information leakage (Li, 2010; Verrecchia and Weber, 2006; Ali, Klasa and Yeung, 2014; Cao et al., 2018). As a result, they typically rely on broad proxies for competition pressure, such as the number of competitors based on Text-based Network Industry Classifications (TNIC) data (Hoberg and Phillips, 2016), the existence of trade secrets (Glaeser, 2018), and rivals' R&D (Cao et al., 2018). Notably, Kim and Valen-

tine (2021) verify that mandatory disclosure generates both spillover effects and proprietary costs simultaneously, making broad proxies inadequate.

To address this challenge, I propose a framework that isolates the specific channels through which disclosed information can contribute to the proprietary cost of disclosure. I argue that a true measure of proprietary cost must capture not just the presence of rivals, but also their capacity to learn and the intrinsic value of the exposed asset. More specifically, I decompose competitive exposure into three factors: the number of rivals who can exploit the information, the technology overlap between market competitors, and the novelty of the disclosed information. This approach allows for a clearer understanding of how these factors interact with each other.

Testing this proposed framework requires an industry where competitive proximity can be measured accurately, and a setting where the secrecy advantage of debt changes exogenously. The pharmaceutical industry provides an ideal laboratory. I exploit the 2014 FDA Final Rule, which mandates registration and results-reporting of clinical trials on ClinicalTrials.gov, as an exogenous public information shock to pharmaceutical firms. Before the rule, pharmaceutical startups could protect their competitive edge by keeping failed trial data private or delaying disclosure. The rule forced firms to timely disclose this previously private information to the public, shrinking the gap between what debt and equity reveal. Consequently, to the extent that debt serves as a secrecy shield, firms subject to this mandatory disclosure should actively reduce their debt usage, particularly among firms that hold the most valuable proprietary information.

This information disclosure shock allows me to compare the change in debt-taking probability for pharmaceutical startups with trial records (treated group) — who are directly exposed to the disclosure mandate — to pharma startups without any trial records (control group). To capture a rival's absorptive capacity, I construct a measure of chemical similarity. This aligns conceptually with the use of technology/patent overlap in recent finance and accounting literature (e.g., Cao et al., 2018; Lee et al., 2019), but is tailored to the pharma-

ceutical product space. Furthermore, I partition the sample into novel versus follow-on drugs to capture the Content dimension, echoing the literature's recognition that the intrinsic type of information dictates the severity of proprietary costs (Ellis et al., 2012; Glaeser, 2018).

Consistent with the "debt as information shield" hypothesis, the empirical results show the mandatory disclosure shock is associated with 1.5 percentage point decline in venture debt usage among treated firms, a 36% proportional decline relative to the pre-shock mean. To ensure this debt usage decline reflects an active shift in capital structure rather than a general loss of funding supply or demand, I employ a Heckman selection model. Conditioning on securing external financing, the decline remains statistically and economically significant, suggesting this shift is driven by the demand of startups. The results rule out the explanation that this decrease in financing demand is due to R&D slowdown (Cunningham et al., 2025) or a credit supply contraction (Mann, 2018).

Consistent with the "debt as information shield" hypothesis, this debt usage decline is not uniform; it is concentrated where the proprietary cost of disclosure is highest. After the FDA Final Rule, startups in markets with high technological overlap experienced a significantly larger flight from debt: a one-standard-deviation increase in pre-shock market chemical similarity amplifies the post-shock decline in the probability of venture debt taking by 1.8 percentage points. Within these competitive markets, startups developing novel drugs experience a larger decline in venture debt usage than those developing follow-on drugs, consistent with the prediction that genuinely frontier information is costliest to disclose. In contrast, the drug novelty alone does not drive the decline of venture debt usage. Instead, novelty amplifies the effect only conditional on competitive exposure, implying that secrecy preservation is the main incentive that drives debt usage, rather than the alternative channel where the shock simply lowered VC information asymmetry.

Finally, the within-debt decomposition shows that financial instruments that provide marginal secrecy protection are abandoned first when proprietary information value decreases. The empirical evidence shows, within the debt category, convertible debt—which

approaches equity-level due diligence—collapses disproportionately (∼88%), while pure venture debt usage declines moderately (∼53%). Collectively, these findings suggests that the marginal benefit of preserving proprietary information directly shapes entrepreneurial capital structure, rejecting the explanation by Klasa et al. (2018), which argues that firms may deleverage to preserve financial flexibility when facing higher predation risk.

The results survive a battery of robustness tests. Event-study frameworks confirm that pre-trends are flat, validating the parallel trends assumption. To rule out unobserved shocks specific to the pharmaceutical control group, I estimate a triple-difference specification using startups across all other non-pharmaceutical industries as a control, and the competition-amplified results remain robust. Moreover, placebo shock years produce null coefficients, suggesting there are no spurious secular trends. I also use the actual 2017 enforcement date, which yields comparable results. Finally, placebo tests confirm that the decline in venture debt usage is stronger in easily reverse-engineered small-molecule drugs rather than biologics, collectively reinforcing the proprietary cost mechanism.

This paper contributes to the existing literature in three ways. First, it extends the Bhattacharya-Ritter disclosure tradeoff to the instrument-choice margin, showing that firms manage proprietary costs not only by adjusting how much they disclose or who they disclose to, but also by choosing financial instruments that structurally extract less information. Second, it identifies a previously unrecognized motive for venture debt: secrecy preservation. Third, it provides evidence on which dimension of competitive exposure drives proprietary costs: market-level technology overlap is the primary determinant, with information novelty amplifying the effect within competitive markets.

The remainder proceeds as follows. Section 2 reviews the related literature. Section 3 develops the conceptual framework and derives testable predictions. Section 4 describes the institutional setting. Section 5 details data and sample construction. Section 6 presents the empirical methodology and the main results. Section 7 addresses alternative explanations. Section 8 concludes.

2 Literature review

2.1 Proprietary cost of disclosure

Building on the fundamental disclosure tradeoff established by Verrecchia (1983) and Bhattacharya and Ritter (1983), subsequent research demonstrates that firms actively modulate their behavior to mitigate information spillovers. The literature primarily documents two mitigating channels: altering the disclosure itself or altering the audience.

Regarding disclosure alteration, Boone, Floros, and Johnson (2016) find that nearly 40% of IPO firms redact proprietary information from SEC filings; Kankanhalli, Kwan, and Merkley (2024) show that firms with valuable intellectual property (IP) in competitive markets strategically suppress contract terms; Kim and Valentine (2021) document material proprietary costs from mandatory patent disclosures; and Baruffaldi, Simeth, and Wehrheim (2024) show that firms increase scientific publications as an alternative disclosure channel when analyst coverage falls. For audience selection, Yosha (1995) shows that firms prefer bilateral lending to limit the number of informed parties; Bhattacharya and Chiesa (1995) demonstrate that exclusive banking relationships reduce information spillovers; and Asker and Ljungqvist (2010) provide empirical evidence that firms avoid sharing investment banks with product-market competitors because shared intermediaries create leakage channels.

These mitigation strategies shed light on what types of information are valuable and how competitors benefit from disclosed information, reducing the value of the disclosing firm. Recent literature builds direct measurements of these technological spillovers, confirming that technological spillovers are a material threat; rivals actively monitor peer disclosures and use this acquired information to adjust their own corporate investments and product strategies (Bernard et al., 2020; Bustamante and Frésard, 2021). However, Bloom, Schankerman, and Van Reenen (2013) demonstrate that technology spillovers and product market rivalry have opposite effects on firm value, suggesting that this threat of technological spillover operates differently than general product market rivalry. Thus, it is crucial to empirically disentangle

the two to identify the real consequences of increasing disclosure.

Faced with these actionable spillover threats, a nascent strand of literature examines how the choice of the financial instrument itself interacts with proprietary costs. Floros, Sivaramakrishnan, and Zufarov (2024) find that firms with higher proprietary costs prefer private to public equity. Bae et al. (2024) find a similar effect within the debt market, where proprietary costs push firms toward bank loans over bonds. Klasa et al. (2018) show that exogenous increases in trade secret protection lead firms to increase leverage. However, they argue that the motivation for this financial structure change is to avoid being targeted by predatory activities, rather than the change in disclosure cost itself.

Crucially, while this literature acknowledges that capital structure responds to competitive threats, it has not explored this capital structure choice as a strategy to minimize information disclosure in the security origination process. Specifically, the literature has not integrated the fundamental difference in information sensitivity between debt and equity. Foundational security design models establish that standard debt minimizes adverse selection and prevents costly information acquisition (Gorton and Pennacchi, 1990; Boot and Thakor, 1993; DeMarzo and Duffie, 1999). Bertomeu et al. (2011) show that debt minimizes information advantages for informed investors in secondary markets, suggesting that the information sensitivity of financial instrument is a determinant of capital structure. Dang et al. (2012) further show that the information demand between debt and equity is different in the security origination process. My paper addresses this information-sensitivity difference embedded in financing instruments by testing whether the "information shield" function of debt is actively utilized in high-spillover environments.

2.2 Venture debt

The existence of venture debt (hereafter VD) has long been seen as a puzzle. Early research on venture debt documents the growth of startup debt usage and explores the rationales behind it (Ibrahim, 2010; Robb and Robinson, 2014). Morse (2025) classifies venture loans

into patent loans (secured by IP), bridge loans (short-term financing between equity rounds), and leveraged loans (debt added alongside equity), and shows that the venture debt market has expanded to approximately 15% of total startup funding by 2021.

The subsequent literature has proposed several theories for why startups use venture debt, organized around distinct frictions in VC financing. The first strand centers on avoiding equity dilution. Davis, Morse, and Wang (2020) model venture debt as a tool to align incentives between founders and VC investors by enabling riskier operational strategies, and document that recent dilution predicts VD usage. However, their model implies VD should be structured as leveraged debt rather than bridge loans, which is inconsistent with observed practice.

The second strand emphasizes bridge financing and cost reduction. González-Uribe and Mann (2024) show that achieving a new milestone triggers VC fundraising and VD repayment, arguing that venture lenders possess distinct skillsets that allow them to bridge-finance startups at lower cost; they document that general partners (GPs) of venture debt funds have meaningfully different backgrounds from GPs of VC funds.

A third strand of literature suggests that collateralized venture debt lowers the cost of capital. Both Mann (2018) and Hochberg, Serrano, and Ziedonis (2018) document that approximately 36–38% of firms use patents as collateral for venture debt. Mann (2018) provides causal evidence that strengthening creditor rights drives patenting companies to raise more debt.

Finally, Tykvová (2017) proposes that venture debt serves as a quality signal for future fundraising, showing that VD-backed firms have superior subsequent outcomes, though this finding is subject to reverse causality. More recently, Buchner, Espenlaub, Khurshed, and Mohamed (2024) document that venture debt is a relationship-specific business, and Chen and Lyu (2025) show that VC-lender relationships facilitate venture debt access. Both papers demonstrate that the venture debt market is highly private and relationship-driven. Building on this evidence, this paper argues that such an opaque network structure facilitates secrecy

preservation, making it a key incentive for startups to take on venture debt.

As the previous section discussed, literature has largely overlooked the role of product market competition and proprietary disclosure costs in the startup financing context. This paper fills this gap by providing a previously undocumented incentive for venture debt: secrecy preservation. The next section develops a framework to test how firms utilize this instrument-level shield in the presence of the proprietary cost of disclosure.

3 Conceptual Framework

The conceptual framework draws on the information-insensitivity property of debt identified by Dang et al. (2012): because creditors need only verify solvency while equity investors must verify the full upside, debt reveals less about the borrower's private information. The central tension is between the valuation benefit of equity and the secrecy benefit of debt. The financing choice follows from how these two benefits vary with the startup's quality. For low-tech startups, the pricing benefit dominates: they have little proprietary technology at risk, and the VC helps them access capital. For high-tech startups, the secrecy benefit dominates: they have the most to lose from disclosure, and the marginal improvement in equity pricing is small. The lowest-tech startups cannot access debt at all—lenders refuse when the probability of repayment is too low.

Now consider a regulation that forces startups to publicly disclose more information, reducing the quantity of private information. The disclosure shock reduces the incentive for taking venture debt as an "information shield". As a result, startups reduce venture debt usage, replacing it with venture capital financing. Second, the reduction is amplified when competitors have higher information extraction ability, proxied by technology overlap. Third, the reduction is amplified by the value of the incremental proprietary information, which is proxied with novelty. Two additional predictions follow: convertible debt—which requires more disclosure than pure venture debt—loses its secrecy advantage first, and the

shock compresses not only the firm's incentive to take debt, but also the firm's eligibility for debt. The formal model in Section 3.1 further shows these arguments. All proofs appear in Appendix A.

3.1 Formal model

Consider a risk-free economy ($r = 0$) where a startup competes against N rivals for a patent of value V. All firms require external financing of amount I. The game proceeds in three stages: at $t = -1$ the startup is endowed with private technology; at $t = 0$ it chooses a financing instrument, which determines how much proprietary information is disclosed, and rivals update their technology based on the disclosure; at $t = 1$ the patent race resolves. The startup's technology is characterized by a hazard rate $n_i \in [0, +\infty)$, where higher n_i corresponds to better technology. Rivals possess baseline technology $n_0 < n_i$ but can improve by learning from the startup's disclosure.

The key modeling choice is that the financing instrument determines how much information leaks. Total verifiable information about the startup's technology is fixed at $\bar{y} = y_{\text{public}} + y_{\text{private}}$, where y_{public} is already public and y_{private} is the residual proprietary component. Two instruments are available in a competitive financial market, and they impose fundamentally different information demands. A venture debt creditor holds a fixed claim L and needs only to verify that the startup can repay—the solvency state. The information disclosed under debt is therefore minimal: $Y_{\text{debt}} \approx y_{\text{pub}}$. A venture capital investor, by contrast, provides capital I in exchange for equity share $(1-\alpha)$ and must evaluate the full distribution of upside outcomes, requiring $Y_{\text{VC}} \gg Y_{\text{debt}}$ and leaving essentially no proprietary information undisclosed ($y^{\text{VC}}_{\text{priv}} \approx 0$). The startup's payoff under each instrument depends on both the terms of financing and the probability of winning the patent race.

Under debt, the startup retains $V - L$ if it wins, giving payoff

$$U_{\text{debt}}(n) = (V - L) \cdot \Pi_i(Y_{\text{debt}}) \tag{1}$$

where L is the fixed debt repayment and Π_i is the probability of winning. Under equity, the startup retains share $\alpha(n)$ of the prize, giving payoff

$$U_{\text{VC}}(n) = \alpha(n) \cdot V \cdot \Pi_i(Y_{\text{VC}}) \tag{2}$$

where $\alpha(n)$ is the startup's retained equity share after VC due diligence.

The win probability, in turn, depends on how much rivals learn from the startup's disclosure. Each rival observes the disclosed information Y and updates its hazard rate to $n_{\text{rival}}(Y) = n_0 + \lambda\psi Y$, where $\lambda \in [0, 1]$ is technology overlap—how similar the rival's R&D program is to the startup's—and $\psi \in [0, 1]$ is information novelty—how much the disclosed results advance the frontier beyond what rivals already know. Since all N rivals update simultaneously, the startup's win probability is

$$\Pi_i(Y) = \frac{n_i}{n_i + N(n_0 + \lambda\psi Y)} \tag{3}$$

This expression makes precise the competitive cost of disclosure: higher Y raises each rival's hazard rate, lowering the startup's win probability. The cost is amplified by the number of rivals (N), their technology overlap (λ), and the novelty of the disclosed information (ψ). Because $Y_{\text{VC}} \gg Y_{\text{debt}}$, equity financing imposes a strictly larger competitive cost than debt.

The remaining ingredient is how equity pricing varies with startup quality. I assume that $\alpha(n)$ is increasing and concave in n_i, with $\alpha(0) > 0$ and $\lim_{n\to\infty} \alpha(n) = \bar{\alpha} < (V - L)/V$. The VC's due diligence reveals the startup's type, so better startups negotiate better terms ($\alpha' > 0$), but with diminishing gains ($\alpha'' \leq 0$). The upper bound $\bar{\alpha} < (V - L)/V$ ensures that even the best startup cannot negotiate equity terms that dominate debt on both pricing and secrecy margins. This is empirically mild: it says venture debt is cheaper per dollar than equity for firms that can access it.

With these elements in place, I can characterize the equilibrium. Define aggregate rival

threat under each instrument as $\Lambda_{\text{debt}} \equiv N(n_0 + \lambda\psi Y_{\text{debt}})$ and $\Lambda_{\text{VC}} \equiv N(n_0 + \lambda\psi Y_{\text{VC}})$. Since $Y_{\text{VC}} > Y_{\text{debt}}$, I have $\Lambda_{\text{VC}} > \Lambda_{\text{debt}}$: rivals learn more under equity. The lender participates when the expected repayment covers the investment: $L \cdot \Pi_i(Y_{\text{debt}}) \geq I$, which requires $n_i \geq n_L \equiv I\Lambda_{\text{debt}}/(L - I)$ (Appendix A.1). Conditional on debt being feasible, the startup prefers debt when

$$\Delta(n) \equiv (V - L) \cdot \frac{n}{n + \Lambda_{\text{debt}}} - \alpha(n)V \cdot \frac{n}{n + \Lambda_{\text{VC}}} \geq 0 \tag{4}$$

Two forces shape this payoff difference. The first term captures the secrecy benefit of debt: because debt discloses less, the startup faces weaker rivals and wins more often ($\Lambda_{\text{debt}} < \Lambda_{\text{VC}}$). The second term captures the pricing benefit of equity: because equity reveals the startup's type, better startups negotiate better terms. The tension between these two forces determines the financing choice. Because $\alpha(n)$ is concave, the pricing benefit has diminishing returns—the marginal improvement in equity terms shrinks as the startup gets stronger. The secrecy benefit, by contrast, remains large for high-n_i firms because they have the most proprietary technology at risk. Under the assumption that $\alpha(n)$ is increasing and concave in n_i, $\Delta(n)$ crosses zero exactly once from below at a unique threshold n^* (Appendix A.2), generating three regimes:

- In Regime I ($n_i < n_L$), the lender's participation constraint is violated and the startup must use equity.
- In Regime II ($n_L \leq n_i < n^*$), debt is feasible but the pricing benefit of equity exceeds the secrecy benefit of debt, so the startup voluntarily chooses equity.
- In Regime III ($n_i \geq n^*$), the secrecy benefit dominates and the startup prefers debt.

The role of competition is non-monotonic. Moderate competition raises the value of secrecy, making debt more attractive. While extreme competition eliminates debt usage: under limited liability, as $N \to \infty$ both payoffs converge to zero, and the lender's cutoff n_L

(which is linear in N) eventually exceeds any finite n_i, forcing the startup into Regime I (Appendix A.3).

3.2 Impact of Disclosure Shock

Now consider the effect of an exogenous increase in mandatory public disclosure—a rise in y_{pub}. Because total verifiable information $\bar{y}$ is fixed, higher y_{pub} mechanically raises Y_{debt} (debt disclosure now includes publicly mandated content) but leaves Y_{VC} unchanged (equity investors already extracted all information). Since $\alpha(n)$ depends on the startup's type rather than on the public mandate, the shock operates entirely through the secrecy channel: it erodes debt's information advantage while leaving equity's terms unaffected.

The first-order effect is a decline in debt's relative attractiveness. Differentiating equation (4) with respect to y_{pub} gives $\partial\Delta/\partial y_{\text{pub}} = -(V-L)nN\lambda\psi/(n+\Lambda_{\text{debt}})^2 < 0$ (Result 1; Appendix A.4). The disclosure shock erodes debt's secrecy advantage for all firms, and the effect vanishes only when $\lambda = 0$ (no technology overlap) or $\psi = 0$ (no novel information), confirming that the mechanism requires both a competitive channel and informational content.

The decline in venture debt usage is not uniform across firms. Technology overlap amplifies the erosion: $\partial^2\Delta/\partial y_{\text{pub}}\,\partial\lambda < 0$ for technologically dominant startups (Result 2; Appendix A.5). Firms whose rivals work in the same chemical space lose more from mandatory disclosure because those rivals can directly exploit the newly public information. By symmetric logic, novelty also amplifies the erosion: $\partial^2\Delta/\partial y_{\text{pub}}\partial\psi < 0$ (Result 3; Appendix A.6). Pioneers—whose disclosed results advance the frontier—lose more than followers whose information is already approximated by prior public knowledge.

Two additional predictions follow from the model's structure. First, within the debt category, instruments that require more information disclosure lose their secrecy advantage first. Convertible debt requires the lender to assess the value of the conversion option—

an upside evaluation approaching equity-level due diligence—and therefore discloses more than pure venture debt. The shock compresses convertible debt's already-narrow secrecy margin before eroding pure VD's larger margin (Corollary 1). Second, the shock compresses the debt-preference band from both sides: the lender's participation threshold rises (lenders require stronger startups) and the indifference threshold n^* rises (more startups find equity preferable). Compression is most severe where both technology overlap and novelty are high (Corollary 2; Appendix A.7).

3.3 Empirical Predictions

Section 4 describes the specific institutional setting and the shock I exploit: the FDA Final Rule in 2014. Section 5 details how the model parameters map to observable data. Here I state the five testable predictions that follow from the model, each linked to the test results in Section 6.

Hypothesis 1 (Post-shock decline). Pharmaceutical startups subject to the FDA Final Rule disclosure shock reduce venture debt usage relative to control firms. Tested by the difference-in-differences between treated and control pharma firms before and after the 2014 FDA announcement.

Hypothesis 2 (Competition amplification). The debt usage decline concentrates in therapeutic markets with high chemical similarity. Tested by interacting the treatment effect with pre-shock market-level similarity measures, which proxy for the technology overlap parameter λ in the model.

Hypothesis 3 (Novelty heterogeneity). Among firms in competitive markets, novel drugs drive the decline more strongly than me-too drugs. Tested by a triple interaction conditioning on competitive exposure and varying the novelty of the firm's pipeline, which proxies for the information novelty parameter ψ.

Hypothesis 4 (Within-debt gradient). The decline is stronger for convertible debt than for pure venture debt. Tested by decomposing the dependent variable by debt sub-

type. The model predicts this ranking because convertible debt requires upside assessment approaching equity-level disclosure, leaving a smaller secrecy margin to erode.

Hypothesis 5 (Biologics placebo). The decline concentrates among small-molecule firms; biologics show attenuated effects. Tested by comparing drug types against the control group. Small-molecule drugs have computable chemical structures that make disclosed trial results directly exploitable by competitors, whereas biologics' competitive advantage resides in proprietary manufacturing processes that trial disclosure does not reveal.

4 Institutional Details

4.1 Venture Debt

Startups have long been recognized as an important force for technological development and economic growth. In the process of commercializing unproven technologies, startups are often subject to limited internal resources and seek external financing. However, startups face high uncertainty and information asymmetry, making credibly pledging future cash flows difficult. As a result, debt is widely viewed as unfeasible for young firms (Hall and Lerner, 2010). Despite this conventional view, venture debt plays a significant and growing role in startup finance. Morse (2025) shows that the venture debt market has expanded substantially over the past two decades; by 2021, it accounted for approximately 15% of total startup funding.

Venture debt is typically structured as a short- to medium-term loan, generally ranging from $1–10 million with maturities of 24–36 months and interest rates of 10–15% (Davis et al., 2020). A standard venture debt package consists of four components:

- An upfront fee to arrange the facility
- Interest rates of 7–12% with repayment flexibility
- A back-end and/or final payment fee

- A warrant component, approximately 5–15% of the loan size.

Although the warrant component aligns lender incentives partially with equity upside, the dominant payoff structure remains debt-like: venture lenders are primarily concerned with downside protection, capital structure adequacy, and the likelihood of future refinancing rather than the magnitude of upside returns.

Beyond the payoff structure, the confidential information requirement also distinguishes venture debt from venture capital. During initial deal screening, lenders generally follow credit-market norms and enter non-disclosure agreements (NDAs) prior to due diligence discussions, while venture capital investors, in practice, rarely sign NDAs (Feld and Mendelson, 2019; Morgan Lewis, n.d.; TDK Ventures, 2025). This difference increases the probability of information leakage during equity fundraising relative to debt financing. In addition, the payoff structure of debt creates different incentives for information acquisition: venture capital investors focus on strategic growth and upside potential, whereas creditors emphasize downside protection, capital structure, and the likelihood of future refinancing. Taken together, these features make venture debt an appealing instrument for startups seeking to minimize information leakage during fundraising.

4.2 Drug Development Process

New drug development is a multi-stage, sequential investment process where the core asset—proprietary knowledge—evolves. The process begins with the discovery phase, a high-uncertainty "search" period focused on target identification and high-throughput screening. At this stage, the asset is intangible scientific "know-how," and its value is protected exclusively by trade secrets, as no patentable invention yet exists. The subsequent preclinical phase is the first capital-intensive stage of development, where firms test a lead compound's safety and efficacy in non-human models. After estimating the efficacy and toxicity, firms file the "composition of matter" (molecular) patent and launch clinical trials (clinical phases I-III), a sequential process of human trials to validate safety (Phase I), efficacy (Phase II),

and large-scale statistical confirmation (Phase III). During this process, the firm builds a "patent thicket" of secondary drug patents (e.g., for specific formulations, delivery devices, or new indications) to protect the final commercial product. The entire trajectory, from discovery through approval, typically spans more than a decade, with estimated total costs ranging from $100 million to over $1 billion (DiMasi et al., 2003; Adams and Brantner, 2006; Morgan et al., 2011; Dubois et al., 2015).

Because development is capital-intensive and internally financed resources are limited, pharmaceutical startups must raise external financing repeatedly throughout the clinical process. Each financing event creates a potential channel through which proprietary information—trial designs, efficacy signals, formulation strategies—may leak to competitors, either directly through investor networks or indirectly through the due diligence process.

4.3 The FDA final rule

Public disclosure of clinical trial results has historically been incomplete and biased toward favorable outcomes. To address this, the FDA created the online repository ClinicalTrials.gov in 2000. In 2007, the FDA Amendments Act (FDAAA) required registration of Phase II and later trials for FDA-regulated products. However, the 2007 regulations left reporting standards vague and, critically, exempted trials of drugs that had not received FDA approval (Zarin et al., 2017; DeVito et al., 2020). As a result, compliance remained low: Anderson et al. (2015) find that only 13.4% of trials between 2008 and 2013 met FDAAA reporting requirements.

The FDA announced the "Final Rule" (hereafter FR) amendment in September 2014, enforced on January 18, 2017. The FR introduced two changes that are central to my identification strategy. First, it extended mandatory results reporting to all applicable clinical trials regardless of FDA approval status, closing the loophole that had allowed firms to withhold results from unsuccessful or abandoned programs. Second, it substantially expanded the required detail of both registrations and results: firms must now report participant flow,

baseline characteristics, outcome measures with specific metrics and time points, adverse events including deaths, and full study protocols and statistical analysis plans (SAPs)—all within one year of the primary completion date. Registrations must be submitted within 21 days of the first participant enrollment. Miller et al. (2017) find that compliance rose sharply: for trials in 2014, a median of 100% of FDAAA-applicable trials were compliant. Cunningham et al. (2025) provide evidence that this mandatory disclosure altered the information environment with real operational consequences: They find that the resulting transparency incentivizes a "wait-and-see" approach, leading to a significant slowdown in overall pharmaceutical R&D.

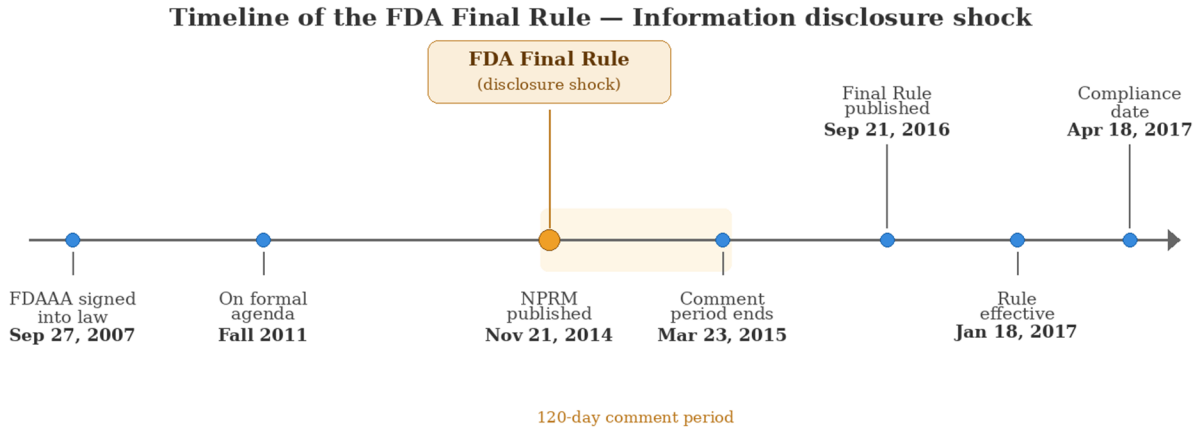


Figure 1: FDA Final Rule timeline

Together, these provisions create an exogenous shock to the pharmaceutical industry's information environment. Before the Final Rule, firms could protect their competitive position by keeping sensitive trial data private. By mandating full disclosure, the rule effectively forces once-proprietary information into the public domain.

5 Data and Sample Construction

As the conceptual framework shows, testing how proprietary information costs affect pharmaceutical startup financing requires two datasets: deal-level records on startup financing activity and drug development records in the pharmaceutical industry. I draw this information from three sources: PitchBook for financing events, ClinicalTrials.gov for clinical trial records and pipeline identification, and PubChem (NIH) for molecular structure data used in chemical similarity calculations.

5.1 Proprietary information cost measurement

As previously discussed, to test how proprietary information costs affect startup financing, I construct three proxies on proprietary cost of disclosure: the number of rivals, the degree of technology overlap with those rivals, and the novelty of the firm's own technology. ClinicalTrials.gov, maintained by the National Library of Medicine, is the primary federal registry for clinical studies. Sponsors of applicable clinical trials must register trials of FDA-regulated drugs and devices, reporting sponsor identity, intervention names, trial phase, condition terms, and enrollment dates. I use ClinicalTrials.gov as the primary source for identifying firms' clinical pipelines, trial phases, and therapeutic markets. I supplement pre-2007 coverage with other public filings, including regulatory filings, press releases, and company disclosures to mitigate the incomplete registration during the voluntary reporting period.

5.1.1 Rival identification

The first step is to identify a startup's competitors. Following Krieger, Li, and Papanikolaou (2022), I use ICD-9 as the primary identifier for competition. In ClinicalTrials.gov, each registered trial reports condition terms that represent the specific medical conditions the intervention targets. Drugs targeting the same condition act as functional substitutes. I map

these condition terms to ICD-9 codes following standard medical classification crosswalks and define a drug's competitors as all other ongoing clinical projects sharing the same ICD-9 code, as these firms are effectively competing for the same patient pool. For each firm-quarter, I calculate LnCompDrugs as the log count of competing drugs in the same therapeutic market.

5.1.2 Project-level similarity metrics

Following Krieger, Li, and Papanikolaou (2022), I construct measures of drug-level novelty and potential knowledge spillover based on drug molecular structural similarity. I obtain molecular structures (SMILES strings) for each drug candidate by linking ClinicalTrials.gov intervention names to PubChem compound records. For each drug pair, I compute pairwise structural similarity using the Tanimoto coefficient (a Jaccard similarity metric) based on molecular fingerprints (Nikolova and Jaworska 2004):

$$T_{A,B} \equiv \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{5}$$

This metric ranges from 0 to 1, with higher values indicating greater overlap in chemical fragments. As the chemistry literature shows, structurally similar compounds tend to exhibit similar biological properties (Johnson and Maggiora, 1990). Thus, I assume that drugs with similar structures (high Tanimoto score) function in a similar way, suggesting similar underlying technology. In the proprietary disclosure cost context, a high Tanimoto score means a rival can more directly translate disclosed trial results into its own R&D program.

Using the drug-pairwise similarity score (Tanimoto score), I develop two similarity measures. The first measure, $MktSim_{k,t}$ proxies for the overall intensity of technology overlap within a therapeutic market. For each ICD-9 market m in quarter t, I compute the average pairwise Tanimoto coefficient among all ongoing clinical-stage drug candidates:

$$\text{MktSim}_{m,t} = \frac{2}{M_{m,t}(M_{m,t} - 1)} \sum_{j<l} T_{j,l} \tag{6}$$

where $M_{m,t}$ is the number of drug candidates with identifiable molecular structures (SMILES) in market m at time t. This symmetric market-level measure captures the technological similarity of the competitive landscape. Higher values represent markets with closer technological substitutes, where disclosed trial results are more broadly exploitable, and the underlying technology is shared by all firms in the ICD-9 market.

The second measure, $HistMaxSim$, captures the novelty of each individual drug project k by measuring its maximum chemical similarity to any previously developed drug in the same market (Krieger, Li and Papanikolaou, 2022):

$$\text{HistMaxSim}_k = \max_{j \in Q(k,m)} T_{k,j} \tag{7}$$

where $Q_{k,m}$ is the set of all molecules in market m that reached Phase 1 clinical trials before candidate k was introduced. A high $HistMaxSim$ indicates a me-too drug that closely resembles existing compounds—its trial results are unlikely to reveal much that competitors do not already know. A low value indicates a genuinely novel molecule whose results would advance the frontier and be more informative to rivals.

5.1.3 Firm-year level aggregation

To match with the firm-year panel of PitchBook deal data. I aggregate these similarity metrics to the firm-year level following a two-step aggregating process: First, I average the quarterly scores to obtain annual values for each drug project. Second, I average across all active projects $P_{i,t}$ within firm i's portfolio:

$$\text{MktSim}_{i,t} = \frac{1}{N} \sum_{k \in P(i,t)} \text{MktSim}_{m(k),t} \tag{8}$$

$$\text{HistSim}_{i,t} = \frac{1}{N} \sum_{k \in P(i,t)} \text{HistMaxSim}_k \tag{9}$$

where $\text{P}_{\text{i,t}}$ is the set of firm i's active drug candidates, m(k) denotes the ICD-9 market

of project k, and $N = |P_{i,t}|$.

To ensure that post-shock changes in pipeline composition do not contaminate the competition proxies, I collapse these firm-year measures to pre-shock averages over 2009–2013 and hold them fixed throughout the sample. I also verified that within-firm standard deviations of these measurements are near zero, confirming that identification exploits persistent cross-sectional differences rather than time-varying competition.

Beyond these baseline measures, I constructed three additional variables: First, I calculate $PhaseGap$, defined as the gap between project k's current trial stage and the market's leading-progress trial stage. Second, I build a composite disclosure risk exposure measure $RivalThreat$ by multiplying market similarity with the number of drugs in the same ICD-9 market. This interaction highlights that the cost of proprietary information is driven by both the number of rivals who can exploit the information and the ability of each rival to extract value from the disclosure. Third, I define a binary indicator $HighThreat$ equal to 1 for a treated firm whose $\ln(RivalThreat)$ exceeds the median. Finally, I create z-scored versions of all variables, standardized using the treated-firm distribution.

5.1.4 Summary statistics

The main restriction of this Tanimoto coefficient approach is that it requires that each drug candidate possess a well-defined chemical structure encoded as a Simplified Molecular-Input Line-Entry System (SMILES) string. This prerequisite restricts the similarity measures to small-molecule compounds; biologics—such as monoclonal antibodies, recombinant proteins, and gene therapies—lack canonical SMILES representations and are therefore excluded from all similarity-based calculations.

This is where market-level information extraction measurement $MktSim$ has advantages. Compared with a firm-specific technology overlap measurement, $MktSim$ allows me to preserve firms that do not develop small molecule drugs, while still being able to observe the market technology overlap. Table 1, Panel A reports the data coverage and distributional

properties of the information leakage risk measures. MktSim and PhaseGap have the broadest coverage, each yielding approximately 7,900–7,960 firm-years out of a full treated panel of 12,960. $HistSim$ has notably lower coverage than $MktSim$ (approximately 3,900 firm-years) because computing it requires a firm to have identifiable molecules with SMILES structures in earlier periods. Thus, both first-in-class innovators and biologics are excluded.

Panel B reports the correlation structure across these measurements. All count-based and phase-based proxies exhibit pairwise correlations of 0.87–0.97, confirming that they capture overlapping dimensions of information leakage breadth. $LnCompDrugs_z$ is highly correlated with $MktSim_z$, suggesting strategic followers entering technological similar markets. $HistSim$ is notably less correlated with the remaining measures ($\rho = 0.39$–0.47), providing empirical confirmation that it captures the novelty dimension rather than the market-level information spillover effect. This low correlation is central to the identification strategy: the $HistSim \times HighThreat$ interaction serves as the primary test that distinguishes the information-leakage channel from alternative explanations based on predatory behavior.

5.2 Sample construction

My deal sample construction starts from PitchBook, the leading database for startup financing. PitchBook provides deal-level financing records including deal and firm characteristics such as deal type, deal size, investor identities, financing round classification, etc. I begin with identifying all firms with at least one venture capital financing activity in PitchBook from 1990 to 2023, excluding firms in finance, real estate, insurance, government, and utility industries. To define the startup financing lifecycle window, I set the start date as the first observable deal date in PitchBook, and the end date as the earliest of: (1) exit date (M&A, IPO, buyout, or bankruptcy), (2) last VC deal date, or (3) 20 years after the founding year. These conditions help me restrict the sample to startups that face the tradeoff between venture debt and venture capital, rather than more established firms that take debt for LBO, M&A, or IPO. I extract all debt and equity financing deals for these firms, classify each deal

as venture debt or VC equity based on PitchBook's deal type field, supplemented by synopsis-based reclassification for ambiguous cases. Lastly, I further expanded the startup-deal panel to a firm-year lifecycle panel.

I restrict the analysis window to 2000–2017 for three reasons. Both venture debt deal volume and drug pipeline records are sparse before 2000, making earlier years unreliable for identification. I conclude the sample period in 2017 to preclude the effect of the 21st Century Cures Act (signed in December 2016), which altered the landscape for novel therapeutics and could confound my drug-novelty heterogeneity tests. In robustness test, I expanded the sample to 2019 (before the COVID-19 pandemic). The competition effect strengthens, while the novelty effect attenuates. Table 2 summarizes the observation changes throughout the sample construction process.

The last step is to merge the pharmaceutical trail dataset with all PitchBook firms in the pharma industry. I first use PitchBook industry codes to identify pharmaceutical firms. Then I apply a two-stage name matching procedure: First, doing an exact match after cleanco normalization (5,427 matches), then applying TF-IDF entity match with first-token edit distance constraint (1,154 matches), yielding 6,581 matched firms. I define the treated group as firms with at least one clinical trial record throughout the sample period. The underlying assumption is that firms with trial records are likely to be affected by the FDA Final Rule. The final sample consists of three groups: 97,378 non-pharmaceutical firms, 3,622 pharmaceutical firms without clinical trial records (control group), and 2,991 pharmaceutical firms with clinical trial data (treated group).

5.3 Descriptive results

Before turning to formal estimation, I document patterns in the raw data that preview the main results. Table 4 reports pre-shock (2000–2013) characteristics across the three groups. Treated pharmaceutical firms are slightly older on average (5.1 years vs. 4.7 years for pharma controls and 4.3 years for non-pharma), have raised more prior capital, and are more likely

to be US-based. These differences suggest that firms with active clinical trial programs are further along the capital-intensive drug development path. Moreover, treated firms utilize more venture debt (4.3% conditional on financing) than both pharma controls (2.6%) and non-pharma firms (2.1%). This is consistent with the secrecy motive: firms with active drug pipelines create more proprietary information, and thus exhibit the greatest demand for debt financing. Venture debt usage monotonically increases with financing maturity across the full sample (rising from 0.9% at Round 1 to over 10% by Round 6), suggesting intangible assets as collateral may play a role (Hochberg et al., 2018).

The divergence of debt usage between the pharmaceutical startups with clinical trial records and the pharmaceutical startups without clinical trial records arises after 2014. Following the FDA shock, treated firms' conditional VD rate drops sharply from 4.3% to 2.7% (a 36% proportional decline), while control groups show no comparable movement (Table 3). Crucially, this decline is not driven by a contraction in credit supply or overall financing access. This indicates that the reduction in VD reflects a deliberate shift in instrument choice among financed firms, rather than a broad tightening of capital availability.

The composition of venture debt deals (Table 3, Panel C) provides further descriptive support for the information channel. Among treated pharma firms, pure venture debt experiences a 53% proportional decline post-shock, while convertible debt collapses by 88%. If the shock increases the predatory risk of startups, leading to deleveraging (Klasa et al., 2018), then convertible debt should be more resilient, as it offers borrowers greater financial flexibility. Instead, the disproportionate collapse of convertible debt suggests that once regulatory mandates force startups to publicly disclose clinical data, the informational advantage of hybrid financial instruments diminishes, pushing firms to abandon debt-like structures entirely.

Finally, among treated pharma startups, the post-shock decline in VD usage is most severe at startups with intermediate clinical development stages. The VD rate drops from 5.5% to 3.0% in Phase 1–2, and from 5.9% to 0.5% in Phase 2–3. This phase gradient aligns

with the proprietary cost tradeoff: intermediate phases are precisely when clinical data is most competitively informative to rivals, yet the drug has not yet reached the final approval stage, where comprehensive public disclosure is unavoidable.

In summary, these descriptive patterns support my "debt as information shield" hypothesis: once regulatory mandates destroy the secrecy premium of debt, the demand for venture debt collapses. The raw data suggests that the flight from venture debt is concentrated where proprietary costs are highest. Section 6 introduces the formal empirical framework to test whether these dynamics hold when controlling for firm characteristics and selection biases.

6 Empirical Tests

6.1 Baseline Difference-in-Differences

As previously discussed, my test starts with verifying if the FDA Final Rule impacts the treated pharmaceutical firms' venture debt usage, as well as other external financing probability, with a simple linear probability model on the pharmaceutical firm-year panel:

$$P(VD_{it} = 1) = \alpha + \beta_1 \, Post_i + \beta_2 \, Post_t \times Treated_i + \beta_3 \, Treated_i + X'_{it}\gamma + \delta_t + \mu_s + \nu_k + \varepsilon_{it} \quad (10)$$

where VD_{it} is an indicator for firm i having at least one venture debt deal in year t; $Post_t$ equals one for years 2014–2017; $Treated_i$ indicates pharma firms matched to clinical trial records; Controls (X_{it}) include log firm age, log previous capital raised, lagged VC round indicators, average trial phase, an indicator for having phase data, log competitor drug count, missingness indicators for $HistSim$ and $MktSim$, log lagged lead investor experience, and a top-30 VC indicator. Fixed effects δ_t, μ_s, and ν_k absorb year, state, and lead investor type variation. Standard errors are two-way clustered at the firm and year level.

Table 5, Column 2 reports a decline of 1.04 percentage points in VD usage among treated

firms, significant at the 1% level. Column 1 shows that overall financing probability also declines by 3.2%, while Column 3 shows VC equity falls in parallel (-2.58%). The results verify my Hypothesis 1. Table 5, Column 4 provides further support for the "debt as information shield" story. I split the treated group into two groups: $Bio\&Pioneer$ firms and $SMILES$ firms—where $Bio\&Pioneer$ indicates treated firms for whom HistSim could not be computed, and $SMILES$ indicates small-molecule firms with computable chemical similarity.

The biomedical literature shows that biologics are over 100 times larger and rely entirely on complex, proprietary biological manufacturing processes (Price and Rai, 2016; Feldman, 2022; Grabowski et al., 2014). Because the manufacturing process itself constitutes the primary barrier to replication (Van de Wiele et al., 2022), clinical trial disclosures yield far less actionable, extractable information for biologic rivals. Thus, I would expect biological firms to be less sensitive to the FDA final rule than traditional small-molecule firms. The prediction for pioneering firms is ambiguous. On the one hand, as the most novel firms, if there is no entry barrier, they might be extremely sensitive to the FDA Final Rule. On the other hand, if the entry barrier is large, then they may not be impacted by the shock, as there are no competitors. In the real world, I expect that the presence of pioneer firms would strengthen the estimated sensitivity to the shock.

The natural disclosure sensitivity difference between biological firms and small-molecular firms provides a quasi-experimental environment. Table 5, Column 4 shows that small-molecule firms show a decline of 1.6 percentage points, while Novel biologics and pioneer firms show a decline of 0.6 percentage points, marginally significant. Small-molecule firms decline approximately 1.7 times more, consistent with the prediction that clinical trial disclosure reveals more competitively actionable information for small molecules whose chemistry is directly benchmarkable.

6.2 Heckman Method and Selection Correction

However, these unconditional baseline results remain susceptible to alternative economic interpretations. Most notably, mandatory disclosure might invite product-market predation by established incumbents. These startups may be rationed out of the capital market, leading to a drop in both debt and equity financing. To address this concern, I employ a Heckman two-stage procedure to disentangle the extensive margin (whether a startup obtains external financing at all) and the intensive margin (conditional on taking external financing, whether a startup chooses debt over equity). Using the pharmaceutical firm-year panel, the first stage estimates the probability of a firm obtaining any external financing. From this, I compute the Inverse Mills Ratio (IMR), which captures omitted variables driving a firm's selection into the sample. Then I include the IMR as a control variable in the second-stage deal panel regression. The IMR absorbs the unobserved firm-level characteristics that correlate with both the likelihood of securing financing and the preference for debt, mitigating the selection bias in conditional estimation.

The first stage estimates a probit for obtaining any financing on the pharma firm-year panel:

$$\begin{aligned} P(\text{Fin}_{it} = 1) = \Phi\big(&\alpha + \beta_1\, Post_t + \beta_2\, Treated_i + \beta_3\, Post_t \times Treated_i + X_{it}'\gamma \\ &+ \delta \cdot \ln(StateVC_{st}) + \delta_t + \mu_s + \varepsilon_{it}\big) \end{aligned} \tag{11}$$

where controls (X_{it}) include log firm age, log previous capital raised, lagged VC round indicators, log competitor drug count, missingness indicators for HistSim, log lagged lead investor experience, and a top-30 VC indicator. Fixed effects δ_t, μ_s, and ν_k absorb year, state, and lead investor type variation. Standard errors are clustered at the firm level.

The exclusion restriction is $ln(StateVC_{st})$, the log of the total number of venture capital deals closed in the state s during the year t across all industries in PitchBook. The first-stage coefficient on $\ln(StateVC_{st})$ is positive and significant at the 1% level, confirming its

relevance (Table 6). One concern about the underlying assumption is that the local VC market only impacts the probability of a startup raising external funds without impacting their choice between debt and equity. This assumption could be violated. For example, if fluctuations in state-level VC supply systematically alter the bargaining power between equity investors and venture lenders, it could influence the intensive margin. Although I cannot fully rule out this possibility, three considerations help mitigate the concern. First, Chen and Lyu (2025) show that venture lending relationships operate through firm-specific VC connections, suggesting the venture debt supply comoves with venture capital supply. Second, I include state fixed effects, which absorb time-invariant differences in local financial infrastructure; the exclusion restriction is identified from within-state, across-time variation in VC supply. Third, the coefficient on IMR is small and insignificant in every second-stage specification reported below, which indicates that unobserved selection into the financing sample does not bias the conditional capital structure choice, suggesting that even if the instrument is imperfect, selection bias does not drive the main results. The intensive-margin results are the same with and without the Heckman correction.

Then the predicted inverse Mills ratio (IMR_{it}) from the first stage enters the deal-level second stage as an additional control:

$$\begin{aligned} P(VD_{it} = 1 \mid \text{Financed}_{it} = 1) = \alpha + \beta_1 \, Post_t + \beta_2 \, Treated_i + \beta_3 \, Post_t \times Treated_i \\ + X_{it}'\gamma + \lambda \cdot IMR_{it} + \delta_t + \mu_s + \nu_k + \varepsilon_{it} \end{aligned} \tag{12}$$

where the deal-level control vector X_it includes log firm age, log previous capital raised, lagged VC round indicators, average trial phase, a pipeline data indicator, $HistSim$ and $MktSim$ missingness indicators, log lagged lead investor experience, and a top-30 VC indicator. Year, state, and lagged lead investor type fixed effects are included. Standard errors are two-way clustered at the firm and year level.

Table 7, Column 1 confirms that the treatment effect is robust to selection bias correction. Following the FDA Final Rule, treated firms significantly decrease their debt usage by 1.5%,

a 36% decline relative to the pre-shock conditional VD rate of 4.3%. The coefficient on the Inverse Mills Ratio is small and statistically insignificant (-0.0098, $p > 0.10$), confirming that unobserved selection into the financing sample does not drive the capital structure changes. Taken together, this evidence indicates that mandatory disclosure drives startups to actively substitute venture debt for venture capital.

6.2.1 Competition Amplification

To probe the proprietary cost of disclosure channel, I exploit differences among startups in the technology overlap. As Hypothesis 2 predicts that the decline should concentrate among firms with the greatest information leakage risk, I augment the conditional, deal-level specification with pre-shock technology overlap interactions.

$$\begin{aligned} P(VD_{it} = 1 \mid Fin_{it} = 1) = \alpha &+ \beta_1 Post_t + \beta_2 Treated_i + \beta_3 Post_t \times Treated_i \\ &+ \beta_4 CompMeasure_i + \beta_5 Post_t \times Treated_i \times CompMeasure_i \\ &+ X'_{it}\gamma + \lambda \cdot IMR_{it} + \delta_t + \mu_s + \nu_k + \varepsilon_{it} \end{aligned} \tag{13}$$

where $CompMeasure_i$ is primarily proxied by $MktSim_z$, the standardized average pairwise Tanimoto coefficient among concurrent drugs in the firm's ICD-9 markets.

Table 7, Column 3 shows that the presence of high-technological-overlap rivals is a key driver behind the observed treatment effect. When the triple interaction $Post \times Treated \times MktSim_z$ is introduced, the competition interaction carries a significant negative weight: A one-standard-deviation increase in chemical similarity amplifies the venture debt decline by 1.8 percentage points. This result is reinforced across specifications: Table 7, Column 5 shows a comparable amplification through alternative market competition measurement $PhaseGap_z$ (0.0152, significant at the 1% level), and Table 7, Column 6 confirms that the number of competitors itself drives the effect (0.0054, significant at the 1% level). The High-Threat specification (Table 7, Column 4) yields a directionally consistent but statistically

insignificant interaction (0.0150, SE = 0.0097). Collectively, these results indicate that the decline in venture debt usage is not uniform across treated firms but concentrates where exposure to information leakage is highest.

Furthermore, these results rule out the competing theory that startups use venture debt primarily to signal their quality (Tykvová, 2017). Under this signaling framework, mandatory disclosure should be least informative in markets with high technological overlap. Thus, the signaling theory predicts that firms in highly similar markets should reduce their debt usage less than firms in sparse markets. The empirical evidence contradicts this prediction, supporting the proprietary cost channel.

The last important result in Table 7, Column 3, is that the baseline level coefficient on $MktSim_z$ is significantly positive, suggesting that, prior to the shock, firms exposed to high potential information-leakage risk used more debt than their less-exposed peers. This positive pre-shock sorting contradicts predation theories (Bolton and Scharfstein, 1990; Klasa et al. 2018): if predation risk were the primary concern, startups in high-competition markets would have avoided fixed-claim debt before the shock to minimize financial vulnerability. Collectively, these pre- and post-shock competitive dynamics confirm that the threat of information leakage, rather than predation or signaling, dictates the startups' usage of venture debt.

6.2.2 Novelty Heterogeneity

While competition determines who can exploit a leak, novelty determines how much they can learn. Disclosing clinical data on a highly derivative "me-too" drug reveals little information that competitors do not already possess. In contrast, disclosing data on a genuinely novel molecule maps new territory on the therapeutic frontier. Hypothesis 3 predicts that within competitive markets, highly novel drugs should suffer the greatest proprietary costs, thereby driving the substitution away from venture debt. I test this by adding a triple interaction to the deal-level specification:

$$
\begin{aligned}
P(VD_{it} = 1 \mid Fin_{it} = 1) = \alpha &+ \beta_1 \, Post_t + \beta_2 \, Treated_i + \beta_3 \, Post_t \times Treated_i \\
&+ \beta_4 \, CompMeasure_i + \beta_5 \, Post_t \times Treated_i \times CompMeasure_i \\
&+ \beta_6 \, HistSim_i + \beta_7 \, Post_t \times Treated_i \times HistSim_i \\
&+ \beta_8 \, Post_t \times Treated_i \times CompMeasure_i \times HistSim_i \\
&+ X_{it}'\gamma + \lambda \cdot IMR_{it} + \delta_t + \mu_s + \nu_k + \varepsilon_{it}
\end{aligned}
\tag{14}
$$

Consistent with the theoretical framework, the baseline coefficient for $Post \times HistSim$ is statistically zero, confirming that novelty alone does not drive the flight from venture debt towards venture capital. Table 8, Column 1 shows an important null result: $Post \times Treated \times MktSim_z \times HistSim$ is insignificant, indicating that novel drugs are not sensitive to having rivals that are chemically homogeneous. These results highlight a nuance in how proprietary costs operate. While $MktSim_z$ robustly captures the average technological density of a therapeutic class—making it an ideal proxy for broad product-market competition—it measures undirected threat. For a rival to actively exploit the disclosure of a highly novel drug, they must be clinically positioned to act on that specific data. When capturing this directed vulnerability using relative pipeline position $PhaseGap_z$ (Table 8, Column 2), the triple turns significant and positive (+0.093, significant at the 5% level). The $HighThreat$ specification, which captures the aggregate exposure to information leakage, yields a similar positive coefficient of 0.153, significant at the 10% level (Table 8, Column 3). These results highlight a specific vulnerability in startup finance: the highest proprietary costs are borne by novel followers in crowded markets. Moreover, the fact that this treatment effect is driven by both novelty and competition rules out the competing story that the disclosure shock simply reduced VC information asymmetry (discussed in Section 7.4).

6.2.3 Within-Debt Gradient

The preceding analysis establishes that a startup's flight from debt is dictated by its exposure to information leakage. This mechanism also extends to the design of the financial contracts themselves. Specifically, not all debt instruments offer the same information shield. Pure venture debt requires a lender to verify only downside solvency. Convertible debt, however, requires the lender to value the upside conversion option—a process demanding equity-level due diligence and extensive proprietary disclosure. Hypothesis 4 predicts that if secrecy drives the results, highly information-sensitive convertible debt should collapse the fastest.

To test this, I re-estimate Table 7, Column 3 specification $Post \times Treated \times MktSim_z$, replacing the dependent variable with an indicator for pure VD only, excluding convertible and hybrid debt deals. The result yields a decline of -0.0116 (Table 9, Column 2), which is notably smaller than the all-debt estimate (-0.0181), implying that convertible debt contributes disproportionately to the debt usage decline. Raw transition rates confirm this divergence: post-shock, pure venture debt declines moderately by 53%, while convertible debt collapses by 88% (Table 3, Panel C). This gradient further contradicts the deleveraging story (Klasa et al., 2018)—if firms merely wanted to reduce distress risk, pure debt should have declined the most. Instead, the data show the opposite: the sharpest retreat occurs in instruments that offer the least secrecy protection, confirming that the shift in capital structure is a strategic response to information extraction risk.

6.3 Robustness Tests

6.3.1 Event Studies and Parallel Trends on baseline DiD

To validate the parallel trends assumption of the difference-in-differences design, I replace the single $Post \times Treated$ indicator with year-specific interactions relative to t – 1. Pre-shock coefficients for t – 5 through t – 2 are insignificant except t – 4, which is marginally significant, and the joint F-test cannot reject the null hypothesis of zero pre-trends ($p = 0.867$). Following

the 2014 mandate, the coefficients turn negative immediately at t = 0 (-0.0119, significant at the 1% level) and remain highly significant through t + 3 (-0.0186, significant at the 1% level). Furthermore, an anticipation test using a 2012–2013 early-treatment indicator yields a null coefficient, while the true $Post \times Treated$ retains significance (Table 12, Panel D).

6.3.2 Competition-specific event studies

To ensure the cross-sectional mechanism results are not driven by differential pre-trends among highly competitive firms, I estimate separate event studies interacting each competition proxy with year dummies within the treated sample (Table 13). For the continuous $MktSim_z$ measure, post-shock coefficients generally increase in magnitude, while the pre-period coefficients are jointly insignificant (p = 0.306). $PhaseGap_z$ produces a similarly clean parallel trend (p = 0.365).

The event study for the binary HighThreat specification does exhibit some pre-period volatility, with three out of four pre-period coefficients reaching statistical significance. However, a joint F-test confirms that these year-to-year fluctuations do not constitute a systematic differential pre-trend (p = 0.134), preserving the validity of the estimation. Taken together with the previous baseline results, these findings suggest firms in more competitive markets have consistently different baseline VD rates throughout the sample period. To ensure conservative identification, I rely on $MktSim_z$ and $PhaseGap_z$ for the primary competition-amplification results (Section 6.3) and use $HighThreat$ as a confirmatory measure.

6.3.3 Competition placebo test

I run standalone placebo tests for each competition interaction at fake shock years 2010–2012 on the pharma deal sample (Table 12, Panel B). MktSim_z interaction placebos are uniformly null. HighThreat binary placebos are null at the closest pre-shock year (2012) but show a marginal effect at 2010, consistent with the persistent level effect identified in the

event study rather than a differential trend. The triple-interaction placebo $Post \times Treated \times HighThreat \times HistSim$ is null at all three fake years (Table 12, Panel C), confirming that the novelty moderation of competition emerges specifically at the 2014 shock.

6.3.4 Alternative control group

To rule out the possibility that the baseline results are driven by unobserved shocks specific to the control group (pharma firms without clinical trial record), I use all non-pharmaceutical industries as a second control group in a triple-difference framework (Table 11). As expected, given the pharmaceutical-specific nature of the FDA Final Rule, the average DDD baseline term is insignificant (-0.0025). However, the competition-interacted DDD terms survive: $DDD \times MktSim_z$ = -0.018 (significant at the 1% level) and $DDD \times PhaseGap_z$ = –0.015 (significant at the 1% level). The quadruple interaction $DDD \times HighThreat \times HistSim$ also survives the broader specification (+0.155).

6.3.5 Alternative specifications

Table 14 demonstrates that the findings are robust to a variety of alternative constructions. Using the FDA's 2017 formal enforcement date rather than the 2014 final rule date yields a significant $MktSim_z$ interaction (-0.0181, significant at the 1% level), consistent with firms further adjusting their capital structures upon the rule's enforcement. Replacing the standardized similarity measure with a logarithmic transformation, $ln(1-MktSim)$, yields a perfectly complementary and highly significant interaction ($+0.2398$, significant at the 1% level). Results are robust to the inclusion of lead investor fixed effects (Table 14, Column 4: -0.018) and to dropping the IMR entirely (coefficients identical with and without the Heckman correction).

7 Alternative Explanations

This section discusses all competing explanations and demonstrates how my empirical tests reject each prediction.

7.1 Predation and Financial Flexibility (Klasa et al., 2018)

Klasa et al. (2018) demonstrate that stronger trade secret protection reduces product-market predation risk, allowing firms to safely increase leverage. Conversely, the FDA disclosure mandate increases predation risk, which could theoretically force vulnerable startups to deleverage to preserve financial flexibility.

While this predation channel predicts the same baseline average decline and competition amplification as the secrecy channel, making the two observationally equivalent on these margins, two features of the empirical results break the tie. First, if firms were minimizing financial distress to survive predation, pure venture debt—which creates maximum fixed-claim vulnerability—should decline the most. Instead, convertible debt collapses (∼88%) while pure venture debt proves far more resilient (∼53%). Second, if firms feared predation, competitive startups should have avoided debt even *before* the shock to limit their vulnerability. Instead, these highly competitive firms were the heaviest users of debt pre-shock (significant at the 5% level), a positive sorting dynamic consistent with the secrecy motive but contradictory to predation. In addition, the typical venture debt tranche ($1–$10 million) is generally too small to create massive financial vulnerability for VC-backed startups, and recent work by Pham, Suchard, and Zein (2025) confirms that venture-stage predation operates primarily through VC staging and board representation rather than the debt-equity margin.

7.2 Credit Supply Contraction

An alternative supply-side explanation is that mandatory disclosure devalued the intellectual property serving as collateral for venture lenders (Mann, 2018; Hochberg et al., 2018), or reduced pharmaceutical startups' value due to predatory activities by established incumbents, prompting a contraction in credit supply. The Heckman method I took addresses this extensive margin of credit rationing. As I discussed in section 6.2, the null Inverse Mills Ratio (IMR) in the Heckman selection model confirms that the decline is an intensive-margin choice regarding instrument type, not an extensive-margin refusal by lenders.

7.3 R&D Slowdown and Lower Credit Demand

Recent work by Cunningham et al. (2025) documents that this exact FDA disclosure mandate slowed pharmaceutical R&D, confirming the rule had real economic consequences. If reduced project value or R&D deceleration drove the venture debt decline, firms should theoretically cut all financing—including VC equity—and the decline should be uniform across drug types. My results contradict these predictions. While unconditional results show that overall financing probability drops, conditioning on securing financing reveals a pure instrument substitution effect: the Heckman-corrected deal-level venture debt coefficient is significantly negative while the IMR is null, proving that financed firms are actively shifting from debt to equity rather than uniformly losing access to capital.

7.4 Lower VC information asymmetry: Improved Equity Access, Signaling, and Bridge Financing

As a public information shock, the FDA Final Rule reduces the information asymmetry in the market, making VC more attractive. This higher market transparency may lead to a reduced incentive to signal firm quality (Tykvová 2017), lower cost of due diligence and adverse selection (Davis, Morse, and Wang 2020), and lower demand for bridge financing to

"extend runway" (Gonzalez-Uribe and Mann 2024). My test rejects these alternative stories in three aspects:

First, all three investor-side theories predict an approximately uniform decline across competitive environments, because an improvement in equity access depends on the firm's information environment vis-à-vis its investors, not its product-market rivals. A startup in a niche market benefits from cheaper VC due diligence just as much as a startup in a crowded market. However, the results show that the effect of the standalone treatment is significantly attenuated once competition is controlled for, with the decline concentrated primarily in markets with high chemical similarity. However, this relies on the assumption that firms facing a higher-technology-overlap market do not benefit more from incremental disclosed proprietary information. The following two pieces of evidence further rule out this investor-driven channel.

Under the signaling hypothesis, pure venture debt, which carries maximum fixed-claim exposure, is the strongest signal of quality. If public disclosure replaces this signal, pure debt should decline the most. Instead, pure debt declines 53%, while convertible debt collapses 88%. This disproportionate collapse of convertible debt is also irreconcilable with a reduction in verification costs, as convertible debt requires the most complex valuation (assessing the conversion option) and should theoretically benefit the most from cheaper due diligence.

Finally, if improved equity access were the primary driver, highly novel firms—which inherently face the most severe information asymmetry with outside investors—should exhibit the largest decline regardless of competitive exposure, as they benefit the most from reduced adverse selection. Instead, novelty amplifies the decline strictly conditional on product-market competition. This confirms a channel where capital structure is dictated by how much rivals can extract from the disclosure, rather than how much investors can verify.

8 Conclusion

This study provides novel evidence on the secrecy-preservation role of venture lending, a critical yet under-studied pillar of innovation financing. Consistent with classic disclosure theory, I find that the amount of proprietary information a financial instrument extracts at origination drives the capital structure choice of highly innovative early-stage startups.

Exploiting an exogenous regulatory mandate that forced startups to publicly disclose clinical data, I find that venture debt usage sharply declines when private information diminishes, particularly for firms developing highly novel pipelines in crowded markets. The finding highlights that highly innovative early-stage startups take venture debt to preserve proprietary information, which is consistent with the classic "feedback effect equilibrium" theory (Bhattacharya and Ritter, 1983; Verrecchia, 1983).

The capital structure literature traditionally assumes that the choice between debt and equity is driven by bankruptcy costs, collateral constraints, agency issues, or signaling. My results highlight a different driver: the structural information sensitivity of a financial instruments plays a crucial, friction-reducing role in shielding innovative firms from competitors.

The empirical results also decompose the specific drivers of these proprietary costs. I show that market-level technological overlap absorbs the baseline treatment effect, confirming that the standalone shock to transparency only matters when competition is present. Furthermore, the analysis shows that the proprietary cost of disclosure is jointly determined by the number of competitors, their developmental proximity, and the novelty of the information being revealed.

These findings have two implications. First, mandatory disclosure regulation has a financing-composition cost that existing cost-benefit analysis overlooks. Cunningham et al. (2025) document that the same FDA rule slowed pharmaceutical R&D: a cost measured in reduced innovation output. This paper identifies a second margin: the rule reshapes how surviving innovation is financed, pushing firms toward equity channels that expose proprietary data more broadly. More importantly, this cost is not uniform. It is low for firms in

non-competitive markets, but large for firms in crowded markets. The same transparency mandates therefore impose heterogeneous proprietary costs that depend on the competitive structure of the firm's product market. Disclosure policy may overtax the most innovative firms in the most crowded markets.

Second, the results connect security design theory to startup finance. Dang, Gorton, and Holmström (2012) argue that debt's value lies in its information insensitivity — it trades without requiring the parties to produce or process costly information. The results of the within-debt gradient test suggest a similar preference pattern in private markets. This suggests that the information content of the financing instrument deserves the same attention in the venture capital literature as dilution, collateral, and signaling.

In summary, this paper shows that the demand for venture debt is jointly determined by the information sensitivity of the financial claim and the competitive structure of the firm's product market, highlighting a connection absent from prior capital structure studies of private markets. Moreover, the findings caution that, absent a well-developed infrastructure of lenders willing to provide capital without demanding extensive proprietary access, the economic effects of policies aimed at mandating corporate transparency may inadvertently constrain the financing of highly novel innovation.

9 References

Adams, C.P. and Brantner, V.V., 2006. Estimating the cost of new drug development: Is it really $802 million? *Health Affairs*, 25(2), pp.420-428.

Ali, A., Klasa, S. and Yeung, E., 2014. Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics*, 58(2-3), pp.240-264.

Anderson, M.L. et al., 2015. Compliance with results reporting at ClinicalTrials.gov. *New England Journal of Medicine*, 372(11), pp.1031-1039.

Asker, J. and Ljungqvist, A., 2010. Competition and the structure of vertical relationships in capital markets. *Journal of Political Economy*, 118(3), pp.599-647.

Audretsch, D.B. and Mahmood, T., 1995. New firm survival: new results using a hazard function. *The Review of Economics and Statistics*, pp.97-103.

Bae, K.H., Dai, Y., Tan, W. and Wang, W., 2024. Proprietary information and the choice between public and private debt. *Accounting & Finance*, 64(2), pp.1693-1721.

Baruffaldi, S., Simeth, M. and Wehrheim, L., 2024. The role of scientific publications in innovation disclosure. *Management Science*, 70(1), pp.1-20.

Berger, A.N. and Udell, G.F., 1998. The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, 22(6-8), pp.613-673.

Bernard, D., Blackburne, T. and Thornock, J., 2020. Information flows among rivals and corporate investment. *Journal of Financial Economics*, 136(3), pp.760-779.

Bertomeu, J., Beyer, A. and Dye, R.A., 2011. Capital structure, cost of capital, and voluntary disclosures. *The Accounting Review*, 86(3), pp.857-886.

Bhattacharya, S. and Chiesa, G., 1995. Proprietary information, financial intermediation, and research incentives. *Journal of Financial Intermediation*, 4(4), pp.328-357.

Bhattacharya, S. and Ritter, J.R., 1983. Innovation and communication: Signalling with partial disclosure. *Review of Economic Studies*, 50(2), pp.331-346.

Bloom, N., Schankerman, M. and Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4), pp.1347-1393.

Bolton, P. and Scharfstein, D.S., 1990. A theory of predation based on agency problems in financial contracting. *The American Economic Review*, pp.93-106.

Boone, A.L., Floros, I.V. and Johnson, S.A., 2016. Redacting proprietary information at the initial public offering. *Journal of Financial Economics*, 120(1), pp.102-123.

Boot, A.W. and Thakor, A.V., 1993. Security design. *The Journal of Finance*, 48(4), pp.1349-1378.

Buchner, A., Espenlaub, S., Khurshed, A. and Mohamed, A., 2024. Private debt and the role of venture capital and private equity sponsors. *Management Science*, 70(1), pp.372-395.

Cao, S.S., Ma, G., Tucker, J.W. and Wan, C., 2018. Technological peer pressure and product disclosure. *The Accounting Review*, 93(6), pp.95-126.

Chen, Z. and Lyu, C., 2025. Venture debt and the role of VC-lender relationships. *Working Paper*.

Cunningham, C., Ederer, F., Hodgson, C. and Wang, W., 2025. Clinical trial transparency and innovation. *Working Paper*.

Dang, T.V., Gorton, G. and Holmström, B., 2012. Ignorance, debt and financial crises. *Working Paper*.

Davis, J., Morse, A. and Wang, X., 2020. The leveraging of Silicon Valley. *Working Paper*.

DeMarzo, P. and Duffie, D., 1999. A liquidity-based model of security design. *Econometrica*, 67(1), pp.65-99.

DeVito, N.J. et al., 2020. Compliance with legal requirement to report clinical trial results

on ClinicalTrials.gov. *The Lancet*, 395(10221), pp.361-369.

DiMasi, J.A., Hansen, R.W. and Grabowski, H.G., 2003. The price of innovation: New estimates of drug development costs. *Journal of Health Economics*, 22(2), pp.151-185.

Dubois, P. et al., 2015. Market size and pharmaceutical innovation. *RAND Journal of Economics*, 46(4), pp.844-871.

Ellis, J.A., Fee, C.E. and Thomas, S.E., 2012. Proprietary costs and the disclosure of information about customers. *Journal of Accounting Research*, 50(3), pp.685-727.

Feld, B. and Mendelson, J., 2019. Venture deals: Be smarter than your lawyer and venture capitalist. *John Wiley & Sons.*

Feldman, R., 2022. Trade secrets in biologic medicine: the boundary with patents. *Colum. Sci. & Tech. L. Rev.*, 24, p.1.

Ferreira, D., Manso, G. and Silva, A.C., 2014. Incentives to innovate and the decision to go public or private. *Review of Financial Studies*, 27(1), pp.256-300.

Floros, I.V., Sivaramakrishnan, K. and Zufarov, R., 2024. Proprietary costs and the equity financing choice. *Review of Accounting Studies*, 29(2), pp.1276-1319.

Garfinkel, J.A. and Hammoudeh, S., 2025. Competition and pharmaceutical innovation. *Working Paper.*

Glaeser, S., 2018. The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets. *Journal of Accounting and Economics*, 66(1), pp.163-193.

Gompers, P.A., 2022. Optimal investment, monitoring, and the staging of venture capital. In *Venture Capital* (pp. 285-313). Routledge.

Gorton, G. and Pennacchi, G., 1990. Financial intermediaries and liquidity creation. *The Journal of Finance*, 45(1), pp.49-71.

González-Uribe, J. and Mann, W., 2024. Venture debt as bridge financing. *Working Paper*.

Grabowski, H.G., Guha, R. and Salgado, M., 2014. Regulatory and cost barriers are likely to limit biosimilar development and expected savings in the near future. *Health Affairs*, 33(6), pp.1048-1057.

Graves, B., 2025. Venture capital due diligence: The importance of trade secret protection. *TDK Ventures Blog*. Available at: https://medium.com/tdk-ventures/venture-capital-due-diligence-the-importance-of-trade-secret-protection-2d10e258318e.

Hall, B.H. and Lerner, J., 2010. The financing of R&D and innovation. In *Handbook of the Economics of Innovation*, Vol. 1, pp.609-639.

Hoberg, G. and Phillips, G., 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5), pp.1423-1465.

Hochberg, Y.V., Serrano, C.J. and Ziedonis, R.H., 2018. Patent collateral, investor commitment, and the market for venture lending. *Journal of Financial Economics*, 130(1), pp.74-94.

Ibrahim, D.M., 2010. Debt as venture capital. *University of Illinois Law Review*, 2010(4), pp.1169-1210.

Johnson, M.A. and Maggiora, G.M., 1990. Concepts and applications of molecular similarity. *Wiley*, New York.

Kamepalli, S.K., Rajan, R. and Zingales, L., 2020. Kill zone (No. w27146). *National Bureau of Economic Research*.

Kankanhalli, G., Kwan, A. and Merkley, K., 2024. Proprietary costs and contract redactions. *American Economic Journal: Applied Economics*, 16(4), pp.1-33.

Kaplan, S.N. and Strömberg, P., 2003. Financial contracting theory meets the real world:

An empirical analysis of venture capital contracts. *The Review of Economic Studies*, 70(2), pp.281-315.

Kerr, W.R. and Nanda, R., 2011. Financing constraints and entrepreneurship. *Handbook of Research on Innovation and Entrepreneurship*. Cheltenham: Elgar, pp.88-103.

Kim, J. and Valentine, K., 2021. The innovation consequences of mandatory patent disclosures. *Journal of Accounting and Economics*, 71(2-3), 101381.

Klasa, S., Ortiz-Molina, H., Serfling, M. and Srinivasan, S., 2018. Protection of trade secrets and capital structure decisions. *Journal of Financial Economics*, 128(2), pp.266-286.

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

Lee, C.M., Sun, S.T., Wang, R. and Zhang, R., 2019. Technological links and predictable returns. *Journal of Financial Economics*, 132(3), pp.76-96.

Li, X., 2010. The impacts of product market competition on the quantity and quality of voluntary disclosures. *Review of Accounting Studies*, 15(3), pp.663-711.

Mann, W., 2018. Creditor rights and innovation: Evidence from patent collateral. *Journal of Financial Economics*, 130(1), pp.25-47.

Miller, J.E. et al., 2017. Quantifying the impact of the Final Rule on clinical trial reporting compliance. *BMJ Open*, 7(11), e017722.

Morgan, S. et al., 2011. The cost of drug development: A systematic review. *Health Policy*, 100(1), pp.4-17.

Morgan, Lewis & Bockius LLP, n.d. Should venture capital firms sign NDAs? *Venture Capital & Private Equity Funds Deskbook Series*. Available at: https://www.morganlewis.com/-/media/files/special-topics/vcpefdeskbook/fundoperation/cpefdeskbook_shouldventurecapitalfirmssignndas.pdf.

Morse, A., 2025. The venture debt market. *Working Paper*.

Nikolova, N. and Jaworska, J., 2004. Approaches to measure chemical similarity. *QSAR & Combinatorial Science*, 22(9-10), pp.1006-1026.

Pham, P.K., Suchard, J.A. and Zein, J., 2025. Venture capital and product market predation. *Review of Finance*, forthcoming.

Price, W.N. and Rai, A.K., 2015. Are trade secrets delaying biosimilars?. *Science*, 348(6231), pp.188-189.

Robb, A.M. and Robinson, D.T., 2014. The capital structure decisions of new firms. *Review of Financial Studies*, 27(1), pp.153-179.

Tykvová, T., 2017. When and why do venture-capital-backed companies obtain venture lending? *Journal of Financial and Quantitative Analysis*, 52(3), pp.1049-1080.

Van de Wiele, V.L., Beall, R.F., Kesselheim, A.S. and Sarpatwari, A., 2022. The characteristics of patents impacting availability of biosimilars. *Nature Biotechnology*, 40(1), pp.22-25.

Verrecchia, R.E., 1983. Discretionary disclosure. *Journal of Accounting and Economics*, 5, pp.179-194.

Verrecchia, R.E. and Weber, J., 2006. Redacted disclosure. *Journal of Accounting Research*, 44(4), pp.791-814.

Yosha, O., 1995. Information disclosure costs and the choice of financing source. *Journal of Financial Intermediation*, 4(1), pp.3-20.

Zarin, D.A. et al., 2017. Update on trial registration 11 years after the ICMJE policy was established. *New England Journal of Medicine*, 376(4), pp.383-391.

A Model Derivations

This appendix provides formal proofs of all results stated in Section 3. Section A.1 collects notation and standing assumptions. Sections A.2–A.8 prove each result in sequence. Section A.9 discusses the breadth-versus-depth distinction.

A.1 Notation and Assumptions

A startup with technology n_i competes against N rivals for a patent of value V, requiring external financing of amount I. Two instruments are available: venture debt with fixed repayment $L > I$, and venture capital with retained equity share $\alpha(n_i)$.

Information structure. Total verifiable information is $\bar{y} = y_{\text{pub}} + y_{\text{priv}}$. Debt discloses $Y_{\text{debt}} \approx y_{\text{pub}}$; equity discloses $Y_{\text{VC}} \approx \bar{y}$, so $Y_{\text{VC}} > Y_{\text{debt}}$.

Rival learning. Each rival observes the startup's disclosure Y and updates its hazard rate to

$$n_{\text{rival}}(Y) = n_0 + \lambda\psi Y,$$

where $\lambda \in [0, 1]$ is technology overlap and $\psi \in [0, 1]$ is information novelty.

Win probability. With N rivals updating simultaneously, the startup's probability of winning the patent race is

$$\Pi_i(Y) = \frac{n_i}{n_i + N(n_0 + \lambda\psi Y)}.$$

Aggregate rival threat. Define

$$\Lambda_{\text{debt}} \equiv N(n_0 + \lambda\psi Y_{\text{debt}}), \qquad \Lambda_{\text{VC}} \equiv N(n_0 + \lambda\psi Y_{\text{VC}}).$$

Since $Y_{\text{VC}} > Y_{\text{debt}}$, it follows that $\Lambda_{\text{VC}} > \Lambda_{\text{debt}}$.

Payoffs. The startup's payoff under each instrument is

$$U_{\text{debt}}(n) = (V - L) \cdot \frac{n}{n + \Lambda_{\text{debt}}}, \tag{A0a}$$

$$U_{\text{VC}}(n) = \alpha(n) \cdot V \cdot \frac{n}{n + \Lambda_{\text{VC}}}. \tag{A0b}$$

Assumption on α. The retained equity share $\alpha(n)$ satisfies: (i) $\alpha'(n) > 0$ (better startups negotiate better terms); (ii) $\alpha''(n) \leq 0$ (with diminishing gains); (iii) $\alpha(0) > 0$; and (iv) $\bar{\alpha} \equiv \lim_{n\to\infty} \alpha(n) < (V - L)/V$ (debt is cheaper per dollar for eligible firms).

Payoff difference. The startup prefers debt whenever $\Delta(n) \geq 0$, where

$$\Delta(n) \equiv (V - L)\, \frac{n}{n + \Lambda_{\text{debt}}} - \alpha(n)\, V\, \frac{n}{n + \Lambda_{\text{VC}}}. \tag{A0c}$$

A.2 Lender Participation Constraint

The lender provides I and receives L if the startup wins, so the participation constraint is

$$L \cdot \frac{n_i}{n_i + \Lambda_{\text{debt}}} \geq I.$$

Rearranging:

$$n_i \geq n_L \equiv \frac{I\, \Lambda_{\text{debt}}}{L - I}. \tag{A1}$$

This requires $L > I$.

Comparative statics. The lender threshold is increasing in both technology overlap and novelty:

$$\frac{\partial n_L}{\partial \lambda} = \frac{IN\psi Y_{\text{debt}}}{L - I} > 0, \qquad \frac{\partial n_L}{\partial \psi} = \frac{IN\lambda Y_{\text{debt}}}{L - I} > 0. \tag{A1$'$}$$

Greater technology overlap or higher novelty strengthens rivals through disclosure, reducing the startup's expected win probability. The lender therefore demands a higher-quality borrower to break even. Note that n_L does not depend on $\alpha(\cdot)$ because the lender holds a fixed

claim.

A.3 Indifference Threshold and Single-Crossing

I establish that $\Delta(n)$ crosses zero exactly once from below, generating three equilibrium regimes.

Boundary behavior.

- As $n \to 0$: both $n/(n + \Lambda_{\text{debt}}) \to 0$ and $n/(n + \Lambda_{\text{VC}}) \to 0$, so both terms in (A0c) vanish and $\Delta(n) \to 0$.
- As $n \to \infty$: both win probabilities approach one, so $\Delta(n) \to (V - L) - \bar{\alpha}\, V > 0$ by the assumption $\bar{\alpha} < (V - L)/V$.

Existence of Regime II. I need $\Delta(n) < 0$ for some range of n. At $n = n_L$, the lender's participation constraint binds, so $\Pi_i(Y_{\text{debt}}) = I/L$. The debt payoff is therefore $(V - L)\, I/L$. Because $\Lambda_{\text{VC}} > \Lambda_{\text{debt}}$, the startup wins less often under equity, but the pricing benefit $\alpha(n_L)\, V$ can exceed $V - L$ for medium-quality firms. Specifically, when $Y_{\text{VC}} \gg Y_{\text{debt}}$ (guaranteed by the information architecture), the equity payoff $\alpha(n_L)\, V \cdot n_L/(n_L + \Lambda_{\text{VC}})$ exceeds $(V - L)\, I/L$, yielding $\Delta(n_L) < 0$.

Single crossing. Differentiating (A0c):

$$\Delta'(n) = \underbrace{\frac{(V - L)\, \Lambda_{\text{debt}}}{(n + \Lambda_{\text{debt}})^2}}_{\text{marginal secrecy benefit}} - \underbrace{\frac{\alpha'(n)\, V\, n}{n + \Lambda_{\text{VC}}}}_{\text{marginal pricing gain}} - \underbrace{\frac{\alpha(n)\, V\, \Lambda_{\text{VC}}}{(n + \Lambda_{\text{VC}})^2}}_{\text{inframarginal equity cost}} . \tag{A2}$$

The first term captures the marginal secrecy benefit of debt: as the startup improves, it wins more often under debt's lower disclosure regime. The second and third terms capture the marginal pricing benefit of equity. Because α is concave ($\alpha'' \leq 0$), the pricing benefit grows at a decreasing rate, while the secrecy benefit—driven by the fixed gap $\Lambda_{\text{VC}} - \Lambda_{\text{debt}}$—persists for all n.

Combining these observations: $\Delta(n_L) < 0$, $\Delta(n) \to (V-L) - \bar{\alpha}V > 0$ as $n \to \infty$, and the concavity of α ensures that $\Delta'(n)$ is eventually dominated by the secrecy term. Therefore Δ crosses zero exactly once from below at a unique n^*, yielding three regimes:

- **Regime I** ($n_i < n_L$): Lender refuses; startup must use equity.
- **Regime II** ($n_L \leq n_i < n^*$): Debt is feasible, but equity's pricing benefit dominates; startup voluntarily chooses equity.
- **Regime III** ($n_i \geq n^*$): Secrecy benefit dominates; startup prefers debt.

A.4 Non-Monotonic Competition Effect

Claim. Moderate competition raises the attractiveness of debt, but extreme competition eliminates debt usage.

Proof. Let $a \equiv n_0 + \lambda\psi Y_{\text{debt}}$ and $b \equiv n_0 + \lambda\psi Y_{\text{VC}}$, so $\Lambda_{\text{debt}} = Na$ and $\Lambda_{\text{VC}} = Nb$. Differentiating (A0c) with respect to N:

$$\frac{\partial \Delta}{\partial N} = -\frac{(V-L)\, n\, a}{(n+Na)^2} + \frac{\alpha(n)\, V\, n\, b}{(n+Nb)^2}. \tag{A3}$$

Small N. When N is small, the second term dominates because $b > a$: equity's competitive cost rises faster than debt's. Hence $\partial\Delta/\partial N > 0$—moderate competition makes debt more attractive.

Large N. Under limited liability, as $N \to \infty$, both payoffs converge to zero, so $\Delta(n) \to 0$. Moreover, from (A1), $n_L = INa/(L-I)$ is linear in N: as N grows, n_L eventually exceeds any finite n_i, forcing all startups into Regime I. Extreme competition eliminates debt through lender refusal. □

A.5 Proof of Result 1: Post-Shock Decline

Claim. An exogenous increase in mandatory public disclosure (y_{pub}) reduces the attractiveness of debt: $\partial\Delta/\partial y_{\text{pub}} < 0$.

Proof. The disclosure shock raises Y_{debt} (since $Y_{\text{debt}} \approx y_{\text{pub}}$) but leaves Y_{VC} unchanged (equity investors already extracted all information). In particular:

$$\frac{\partial \Lambda_{\text{debt}}}{\partial y_{\text{pub}}} = N\lambda\psi > 0, \qquad \frac{\partial \Lambda_{\text{VC}}}{\partial y_{\text{pub}}} = 0.$$

Neither $\alpha(n)$ nor Λ_{VC} depends on y_{pub}, so the equity payoff in (A0c) is unaffected. Differentiating the debt payoff:

$$\frac{\partial \Delta}{\partial y_{\text{pub}}} = -\frac{(V-L)\, n\, N\lambda\psi}{(n+\Lambda_{\text{debt}})^2} < 0. \tag{A4}$$

The inequality is strict whenever $\lambda > 0$ and $\psi > 0$, confirming that the mechanism requires both a competitive channel (technology overlap) and informational content (novelty).

Threshold implications. By the implicit function theorem:

$$\frac{\partial n^*}{\partial y_{\text{pub}}} = -\frac{\partial \Delta/\partial y_{\text{pub}}}{\partial \Delta/\partial n}\bigg|_{n^*} > 0,$$

since $\partial\Delta/\partial n > 0$ at n^* (the single-crossing condition from Section A.3). The lender's cutoff also rises: $\partial n_L/\partial y_{\text{pub}} = IN\lambda\psi/(L-I) > 0$. Both thresholds shift upward, compressing the debt-preference region (Regime III). □

A.6 Proof of Result 2: Competition Amplification

Claim. For technologically dominant startups, the erosion of debt's advantage is amplified by technology overlap: $\partial^2\Delta/\partial y_{\text{pub}}\,\partial\lambda < 0$.

Proof. Let $D \equiv n + \Lambda_{\text{debt}}$. Starting from (A4), differentiate with respect to λ:

$$\begin{aligned}\frac{\partial^2 \Delta}{\partial y_{\text{pub}}\, \partial \lambda} &= \frac{\partial}{\partial \lambda}\left[-\frac{(V-L)\, n\, N \lambda \psi}{D^2}\right] \\ &= -(V-L)\, n\, N\psi \left[\frac{1}{D^2} + \lambda \cdot \frac{\partial}{\partial \lambda}\left(\frac{1}{D^2}\right)\right] \\ &= -(V-L)\, n\, N\psi \left[\frac{1}{D^2} - \frac{2\lambda N \psi Y_{\text{debt}}}{D^3}\right],\end{aligned}$$

where the last step uses $\partial D/\partial \lambda = N\psi Y_{\text{debt}}$ and the chain rule $\partial(D^{-2})/\partial \lambda = -2D^{-3} \cdot N\psi Y_{\text{debt}}$. Factoring out $1/D^2$:

$$\frac{\partial^2 \Delta}{\partial y_{\text{pub}}\, \partial \lambda} = -\frac{(V-L)\, n\, N\psi}{D^2}\left[1 - \frac{2\lambda N \psi Y_{\text{debt}}}{D}\right]. \tag{A5}$$

Sign. The expression is negative when the bracketed term is positive, i.e., when $D > 2\lambda N \psi Y_{\text{debt}}$. Since $D = n + N(n_0 + \lambda \psi Y_{\text{debt}})$, this condition holds for technologically dominant startups (large n_i), where n_i dominates the correction term. Firms whose rivals work in the same chemical space lose more from mandatory disclosure because those rivals can directly exploit the newly public information. □

A.7 Proof of Result 3: Novelty Amplification

Claim. For technologically dominant startups, the erosion of debt's advantage is amplified by information novelty: $\partial^2 \Delta / \partial y_{\text{pub}}\, \partial \psi < 0$.

Proof. The derivation is symmetric to Result 2. Starting from (A4), differentiate with respect to ψ. Using $\partial D/\partial \psi = N\lambda Y_{\text{debt}}$ and applying the same product-and-chain-rule steps:

$$\frac{\partial^2 \Delta}{\partial y_{\text{pub}}\, \partial \psi} = -\frac{(V-L)\, n\, N\lambda}{D^2}\left[1 - \frac{2\psi N \lambda Y_{\text{debt}}}{D}\right]. \tag{A6}$$

This is negative for large n_i by the same argument: $D = n + N(n_0 + \lambda \psi Y_{\text{debt}})$ dominates the correction term when n_i is large. Pioneers—whose disclosed results advance the technological

frontier (high ψ)—experience larger erosion of debt's secrecy advantage than followers whose information is already approximated by prior public knowledge. □

A.8 Regime Compression and Within-Debt Gradient

Corollary 1 (Regime compression). The disclosure shock compresses the debt-preference band from both sides. Compression is most severe when both technology overlap and novelty are high.

Proof. Both regime boundaries shift upward under the shock:

$$\frac{\partial n_L}{\partial y_{\text{pub}}} = \frac{IN\lambda\psi}{L-I} > 0, \qquad \frac{\partial n^*}{\partial y_{\text{pub}}} > 0 \ \text{(from Result 1)}. \tag{A7}$$

The cross-derivatives confirm that compression intensifies with both overlap and novelty:

$$\frac{\partial^2 n_L}{\partial y_{\text{pub}}\,\partial\lambda} = \frac{IN\psi}{L-I} > 0, \qquad \frac{\partial^2 n_L}{\partial y_{\text{pub}}\,\partial\psi} = \frac{IN\lambda}{L-I} > 0.$$

For startups in high-overlap, high-novelty markets, the lender demands an increasingly strong borrower (rising n_L) while the startup's own indifference threshold also rises (rising n^*), maximally compressing Regime III. □

Corollary 2 (Within-debt gradient). Convertible debt—which requires upside assessment approaching equity-level disclosure—loses its secrecy advantage before pure venture debt.

Proof. Let Y_{conv} denote the information disclosed under convertible debt, with $Y_{\text{debt}} < Y_{\text{conv}} < Y_{\text{VC}}$, reflecting the additional disclosure needed to value the conversion option. Define $\Lambda_{\text{conv}} \equiv N(n_0 + \lambda\psi Y_{\text{conv}})$, so $\Lambda_{\text{debt}} < \Lambda_{\text{conv}} < \Lambda_{\text{VC}}$.

The secrecy margin of each instrument is the gap between its rival threat and the equity

benchmark Λ_{VC}:

$$\text{Pure VD margin:} \quad \Lambda_{\text{VC}} - \Lambda_{\text{debt}} = N\lambda\psi(Y_{\text{VC}} - Y_{\text{debt}}),$$

$$\text{Convertible margin:} \quad \Lambda_{\text{VC}} - \Lambda_{\text{conv}} = N\lambda\psi(Y_{\text{VC}} - Y_{\text{conv}}).$$

Since $Y_{\text{conv}} > Y_{\text{debt}}$, the convertible's margin is strictly narrower. As the shock raises y_{pub} and compresses all margins, the convertible's already-narrow margin is eroded first. In the limit, when Y_{debt} rises sufficiently close to Y_{conv}, convertible debt offers negligible secrecy advantage over equity, while pure venture debt retains a residual margin. This predicts that convertible debt collapses disproportionately relative to pure venture debt. □

A.9 Breadth vs. Depth

The product $\lambda\psi$ captures the *breadth channel*: how many rivals collectively benefit from disclosure. The cross-derivative $\partial^2\Delta/\partial y_{\text{pub}}\,\partial(\lambda\psi) < 0$ confirms the decline concentrates where both λ and ψ are high.

A complementary *depth channel* may operate at the bilateral level. For a follower (low ψ), the market-level breadth channel is weak. But a single rival with high bilateral similarity λ_j could directly translate disclosed results to its own program. Testing this depth channel requires a firm-specific similarity measure; the empirical analysis in Section 6 focuses on the market-level breadth channel, which has broader data coverage and cleaner identification properties.

B Tables

Table 1: Competition Measures—Summary Statistics and Correlations (Treated Firms)

Panel A: Summary Statistics (pre-shock averages, treated firm-years)

Variable	Firm-yrs (non-miss.)	N firms	Mean	S.D.	Median	High=1	High=0
MktSim	7,934	1,196	0.082	0.069	0.133	3,973	3,961
HistSim	3,939	580	0.109	0.209	0.307	1,968	1,971
PhaseGap	7,960	1,200	3.758	3.270	6.500	3,933	4,027
LnCompDrugs	7,759	1,175	3.302	2.922	—	—	—
RivalThreat ($\lambda \times$N)	7,967	1,201	—	—	3.574	3,958	4,009

Panel B: Pairwise Correlations (z-scored, treated financed deal sample)

	MktSim	HistSim	LnComp	LnRival	PhaseG
MktSim_z	1.000				
HistSim_z	0.467	1.000			
LnCompDrugs_z	0.871	0.414	1.000		
LnRivalThreat_z	0.831	0.404	0.972	1.000	
PhaseGap_z	0.872	0.387	0.916	0.893	1.000

Notes: Panel A reports summary statistics for competition measures computed from pre-shock averages (2009–2013) within treated firm-years. "Firm-yrs (non-miss.)" is the number of treated firm-years for which the measure could be computed; the full treated panel contains approximately 12,960 firm-years. "N firms" is the corresponding number of unique firms. High=1 (High=0) denotes firm-years above (at or below) the median, computed among treated firm-years with non-missing data. HistSim has the highest missingness because computing historical Tanimoto similarity requires a firm to have identifiable molecules with SMILES structures in earlier periods. LnCompDrugs and RivalThreat are continuous measures used only

in z-scored form. Panel B reports pairwise correlations among z-scored measures in the treated financed deal sample.

Table 2: Sample Construction—Sequential Filters

Filter Step	Deals	Firms
Raw PitchBook extract (1990–2023)	1,345,023	—
Exclude finance/RE/insurance/gov/utilities	1,279,887	—
Require $\geq$1 VC deal (VC-backed universe)	713,741	216,570
Lifecycle filters (age $\leq$20, pre-exit, pre-last-VC)	536,015	202,899
Restrict to VC equity + debt deal types	487,045	202,065
Expand to firm-year panel (lifecycle)	407,117 (firm-yrs)	135,817
Restrict to 2000–2017 analysis window	293,864 (firm-yrs)	103,991
Deal panel (2000–2017, inner join)	217,902 (deals)	103,970

Notes: Each row shows the cumulative effect of applying the indicated filter. The firm-year panel expands each firm from first financing through lifecycle endpoint (earliest of exit, last VC deal, or age 20), inserting zero-deal years.

Table 3: Sample Overview: Observation Counts, Venture Debt Rates, and Debt Subtype Composition

Panel A: Firm-Year Panel

Group	Firm-Year Obs	Firm Obs	Num of VD	Num of Financing	VD Rate	VD Rate|Fin
Non-Pharma	270,010	97,378	3,805	179,679	1.41%	2.12%
Control Pharma	11,356	3,622	174	6,820	1.53%	2.55%
Treated	12,498	2,991	262	7,066	2.10%	3.71%
Treated Pre-shock	7,869	1,912	188	4,369	2.39%	4.30%
Treated Post-shock	4,629	1,866	74	2,697	1.60%	2.74%

Panel B: Deal-Level Panel

Group	Deals	Debt	VC Equity	Debt %	Firms
Non-Pharma	203,265	3,966	199,299	2.0%	97,602
Control Pharma	7,437	181	7,256	2.4%	3,621
Treated	7,200	251	6,949	3.5%	2,747
Treated Pre-shock	4,411	182	4,229	4.1%	1,744
Treated Post-shock	2,789	69	2,720	2.5%	1,662

Notes: VD% is the unconditional venture debt rate; VD%|Fin is the rate conditional on having at least one financing event in the year. Pre-shock: 2000–2013; post-shock: 2014–2017.

Panel C: Debt Subtype Composition (Deal-Level, Treated Pharma)

Subtype	Pre-shock	Post-shock	Total	% of Debt	Proportional Decline (%)
Pure VD	120	57	177	70.5%	–52.5%
Convertible Debt	51	6	57	22.7%	–88.2%
Hybrid Debt	11	6	17	6.8%	–45.5%
Total Debt	182	69	251	100%	–62.1%

Notes: Pure VD includes deals classified as venture lending without a conversion feature. Convertible debt includes deals with an explicit equity conversion option. Hybrid debt includes structured debt instruments with non-standard features. Pre-shock: 2000–2013; post-shock: 2014–2017.

Table 4: Pre-Shock Sample Characteristics

Panel A: Pre-Shock Balance (2000–2013, Firm-Year Level)

Variable	Non-Pharma	Control Pharma	Treated
Firm Age	4.25 (3.66)	4.73 (3.68)	5.09 (3.64)
ln(Previous Raised)	0.77 (1.23)	0.77 (1.22)	1.23 (1.51)
VC Round	1.92 (1.37)	1.96 (1.41)	2.22 (1.55)
US-based (%)	55.2%	43.9%	66.7%
Financing Rate (%)	65.4%	58.6%	55.5%
VD Rate (%)	1.6%	1.5%	2.4%
VC Rate (%)	64.3%	57.7%	53.9%
Equity Likeness	0.967 (0.104)	0.975 (0.096)	0.967 (0.131)
Avg Trial Phase	—	—	1.78 (1.48)
ln(Competitor Drugs)	—	—	4.50 (2.26)
Market Similarity (λ)	—	—	0.096 (0.066)
Hist Max Similarity	—	—	0.130 (0.222)
N (firm-years)	123,072	6,206	7,869

Panel B: VD Rate by Trial Phase (Deal-Level, G4 Treated)

Phase	Pre Deals	Pre VD%	Post Deals	Post VD%	Δ
Pre-clinical/P1	1,705	4.3%	1,172	2.6%	–40%
Phase 1–2	799	5.5%	573	3.0%	–45%
Phase 2–3	324	5.9%	185	0.5%	–92%
Phase 3+	33	6.1%	7	14.3%	134%

Notes: Panel A reports means with standard deviations in parentheses for the pre-shock period (2000–2013). "—" indicates variables not applicable to the group. Equity likeness is conditional on

financing. Panel B reports debt deal share by trial phase among G4 treated firm deals, pre- vs. post-shock. Phase 3+ post-shock has too few observations (7 deals) for meaningful comparison.

Table 5: Baseline Treatment Effects on the Firm-Year Panel (Unconditional on Financing)

	(1)	(2)	(3)	(4)
Dep. Var.:	P(Any Fin.)	P(VD)	P(VC)	P(VD): By Drug Type
Post×Treated	−0.0320**	−0.0104***	−0.0258**	
	(0.0125)	(0.0038)	(0.0125)	
Post×Bio&Pioneer				−0.0059*
				(0.0033)
Post×Smiles				−0.0161***
				(0.0055)
is_Treated	Yes	0.0111**	Yes	
		(0.0051)		
is_novel_pharma				0.0303**
				(0.0120)
is_standard_pharma				0.0380***
				(0.0090)
Controls	Yes	Yes	Yes	Yes
Year, State FE	Yes	Yes	Yes	Yes
N	23,854	23,854	23,854	23,854
R^2	0.4279	0.0317	0.4147	0.0319

Notes: All columns estimated on the Treated+Control firm-year panel, unconditional on financing. Dep. Var. in Columns (1)–(3) are indicators for any financing, venture debt, and VC equity, respectively. Column (4) decomposes the VD effect by drug type (Novel = biologics without SMILES; Standard = small-molecule with SMILES). Robust SEs in parentheses.

Table 6: Heckman First Stage—Probit for P(Any Financing)

Variable	Coefficient	Std. Error
Post × Treated	0.0067	(0.0290)
is_Treated	–0.3347***	(0.0360)
ln(Firm Age)	–0.2693***	(0.0086)
ln(Previous Raised)	0.6811***	(0.0152)
ln(Competitor Drugs)	0.0087*	(0.0047)
HistSim_pre_miss	0.1219***	(0.0292)
ln(State VC Supply) [excl. restr.]	0.1155***	(0.0209)
VC Round FE	Yes	
Lead Investor Controls	Yes	
Year, State FE	Yes	
N	23,854	
IMR mean (s.d.)	1.628 (1.126)	

Notes: Probit for P(any financing = 1) on the G2+G4 pharma firm-year panel. DV equals one if the firm has at least one VC equity or venture debt deal in year t. ln(State VC Supply) is the exclusion restriction: it enters the first stage but is excluded from the deal-level second stage. Lagged VC round indicators, log lagged lead investor experience, and a top-30 VC indicator are included but not reported. Standard errors clustered at the firm level in parentheses.

Table 7: Competition Amplification of the Treatment Effect (Deal-Level, Conditional on Financing)

	(1)	(2)	(3)	(4)	(5)	(6)
Spec.:	Baseline	HighMktSim	MktSim_z	HighThreat	PhaseGap_z	LnCompDrugs
Dep. Var.:			$\mathbb{1}$(Debt Deal)			
Post×Treated	−0.0153***	−0.0104**	−0.0190***	−0.0112*	−0.0180***	−0.0001
	(0.0050)	(0.0051)	(0.0053)	(0.0061)	(0.0052)	(0.0068)
is_Treated	0.0239**	0.0186*	−0.0102	0.0273**	0.0191	0.0326**
	(0.0099)	(0.0111)	(0.0216)	(0.0109)	(0.0174)	(0.0158)
HighMktSim		0.0135**				
		(0.0068)				
PxTreated×HighMktSim		−0.0198*				
		(0.0101)				
MktSim_z			0.0208**			
			(0.0106)			
PxTreated×MktSim_z			−0.0181***			
			(0.0057)			
HighThreat				−0.0037		
				(0.0073)		
PxTreated×HighThreat				−0.0150		
				(0.0097)		
PxTreated×PhaseGap_z					−0.0152***	
					(0.0047)	
PxTreated×LnCompDrugs						−0.0054***
						(0.0018)
IMR_pharma	−0.0098	−0.0095	−0.0096	−0.0096	−0.0096	−0.0101
	(0.0123)	(0.0122)	(0.0123)	(0.0122)	(0.0123)	(0.0124)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	15,244	15,244	15,244	15,244	15,244	15,244
R^2	0.0422	0.0426	0.0437	0.0424	0.0430	0.0432

Notes: All columns estimated on the deal-level panel, conditioning on financed observations. DV: $\mathbb{1}$(debt deal). One competition proxy per column to avoid multicollinearity. Controls: ln firm age, ln previous raised, avg_phase, has_phase_data, HistSim_pre_miss, MktSim_pre_miss, Heckman IMR. Two-way clustered SEs (firm and year) in parentheses.

Table 8: Novelty Heterogeneity Within Competitive Markets (Deal-Level, Conditional on Financing)

	(1)	(2)	(3)
Spec.:	MktSim_z × HistSim	PhaseGap_z × HistSim	HighThreat × HistSim
Dep. Var.:		𝟙(Debt Deal)	
Post×Treated	−0.0251	−0.0242	−0.0225
	(0.0261)	(0.0243)	(0.0243)
HistSim	0.0495	0.0401	0.0388
	(0.0391)	(0.0302)	(0.0355)
PxTreated×HistSim	0.0488	−0.0496	−0.0521
	(0.0911)	(0.0681)	(0.0510)
PxTreated×MktSim_z	−0.0199***		
	(0.0072)		
PxTreated×MktZ×HistSim	−0.0192		
	(0.0325)		
PxTreated×PhaseGap_z		−0.0177***	
		(0.0054)	
PxTreated×PGz×HistSim		0.0929**	
		(0.0419)	
PxTreated×HighThreat			−0.0303**
			(0.0131)
PxTreated×HT×HistSim			0.1529*
			(0.0849)
IMR_pharma	−0.0091	−0.0089	−0.0094
	(0.0123)	(0.0127)	(0.0120)
Controls	Yes	Yes	Yes
Year, State FE	Yes	Yes	Yes
N	15,244	15,244	15,244
R^2	0.0440	0.0433	0.0436

Notes: All columns estimated on the deal-level panel, conditioning on financed observations. Competition×HistSim level and HistSim_pre_miss interactions included but not reported. Two-way clustered SEs (firm and year) in parentheses.

Table 9: Within-Debt Gradient (Deal-Level, Conditional on Financing)

	(1)	(2)
Dep. Var.:	𝟙(Any Debt)	𝟙(Pure VD)
Post×Treated	−0.0190***	−0.0154***
	(0.0053)	(0.0042)
is_Treated	−0.0102	−0.0256
	(0.0216)	(0.0195)
MktSim_z	0.0208**	0.0222**
	(0.0106)	(0.0100)
PxTreated×MktSim_z	−0.0181***	−0.0116***
	(0.0057)	(0.0044)
IMR_pharma	−0.0096	0.0008
	(0.0123)	(0.0104)
Controls	Yes	Yes
Year, State FE	Yes	Yes
N	15,244	15,244
R^2	0.0437	0.0397

Notes: Column (1) reproduces Table 7 Column (3) for comparison. Column (2) restricts the dependent variable to pure venture debt, excluding convertible debt. Same sample and controls. Two-way clustered SEs (firm and year) in parentheses.

Table 10: Event Study—Year × Treated Interactions (Deal-Level)

Period	Coefficient	Std. Error	p-value
t – 5	–0.0066	0.0060	0.272
t – 4	0.0096	0.0058	0.095
t – 3	–0.0034	0.0061	0.578
t – 2	0.0052	0.0068	0.447
t – 1 (baseline)	—	—	—
t = 0	–0.0119***	0.0037	0.001
t + 1	–0.0155***	0.0045	0.001
t + 2	–0.0081**	0.0039	0.036
t + 3	–0.0186***	0.0048	<0.001

Notes: Coefficients on Year × Treated interactions relative to t – 1. Joint F-test for pre-period = 0: p = 0.867. Controls and FE as in Table 7, Column (1). N = 15,244.

Table 11: Triple-Difference Estimates Using Non-Pharmaceutical Industries as Control

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:			$\mathbb{1}$(Debt Deal)		
Specification:	Average	DDD×HT	DDD×MktSim_z	DDD×PhaseGap_z	DDD×HT×HistSim
Post×Pharma×Treated	−0.0025	0.0012	−0.0090	−0.0074	0.0039
	(0.0108)	(0.0105)	(0.0119)	(0.0117)	(0.0105)
DDD×HighThreat		−0.0185*			−0.0368***
		(0.0099)			(0.0135)
DDD×MktSim_z			−0.0177***		
			(0.0050)		
DDD×PhaseGap_z				−0.0147***	
				(0.0044)	
DDD×HT×HistSim					0.1549*
					(0.0862)
Controls	Yes	Yes	Yes	Yes	Yes
Year, Industry FE	Yes	Yes	Yes	Yes	Yes
N	217,902	217,902	217,902	217,902	217,902
R^2	0.0317	0.0318	0.0319	0.0318	0.0319

Notes: Lower-order interactions (Post×Pharma, Post×Treated, Pharma×Treated) and controls included but not reported. Column (5) includes HistSim level, DDD×HistSim, and HT×HistSim interactions (not reported). Two-way clustered SEs.

Table 12: Placebo and Anticipation Tests (Deal-Level)

Panel A: DiD / DDD / Pharma DiD Placebos

Fake Shock	DiD	DDD	Pharma DiD
2010	–0.0038	–0.0338	–0.0036
2011	–0.0026	–0.0245	–0.0060
2012	–0.0026	–0.0381***	–0.0024

Panel B: Competition Amplification Placebos

Fake Shock	HighThreat	MktSim_z	Post×Treated
2010	–0.0172*	–0.0096	0.0015
2011	–0.0134	–0.0064	–0.0003
2012	–0.0046	0.0005	–0.0007

Panel C: HT × HistSim Triple Placebos

Fake Shock	HT×HistSim	HighThreat	Post×Treated
2010	0.0857	–0.0302*	0.0108
2011	0.0852	–0.0286	0.0022
2012	0.0722	–0.0188	–0.0015

Panel D: Anticipation Test (2012–2013 Early Treatment)

Variable	Coefficient	Std. Error
Post×Treated (2014+)	–0.0147***	(0.0051)
Antic×Treated (2012–13)	0.0023	(0.0063)
N	15,244	

Variable	Coefficient	Std. Error
R^2	0.0391	

Notes: Panels A–C report coefficients from fake-shock regressions using pre-shock deal samples. Each fake shock year replaces the true 2014 shock date. Panel A uses two-way clustered SEs (firm and year). Panel B reports standalone competition interaction placebos on the pharma deal sample. Panel C reports the triple-interaction placebo. Panel D tests for anticipation effects using a 2012–2013 early-treatment indicator alongside the true Post $\times$ Treated.

Table 13: Competition-Specific Event Studies (Deal-Level, Within G4)

	MktSim_z		PhaseGap_z		HighThreat	
Period	Coef	SE	Coef	SE	Coef	SE
t – 5	–0.0018	(0.0025)	–0.0191	(0.0143)	–0.0105	(0.0227)
t – 4	–0.0163**	(0.0068)	0.0004	(0.0047)	–0.0266***	(0.0026)
t – 3	–0.0232***	(0.0069)	–0.0161***	(0.0031)	–0.0405***	(0.0055)
t – 2	–0.0077	(0.0124)	–0.0125	(0.0105)	–0.0312***	(0.0113)
t – 1	(baseline)		(baseline)		(baseline)	
t = 0	–0.0197***	(0.0067)	–0.0150***	(0.0048)	–0.0235***	(0.0039)
t + 1	–0.0250***	(0.0077)	–0.0229***	(0.0064)	–0.0364***	(0.0101)
t + 2	–0.0193***	(0.0074)	–0.0181***	(0.0059)	–0.0199***	(0.0072)
t + 3	–0.0285***	(0.0069)	–0.0234***	(0.0059)	–0.0168***	(0.0057)
Joint F (pre)	0.306		0.365		0.134	
N	7,807		7,807		7,807	

Notes: Each column reports coefficients on Competition × Year dummies relative to t – 1, estimated within the G4 treated deal sample. MktSim_z and PhaseGap_z are continuous z-scored interactions; HighThreat is a binary indicator. Joint F reports the p-value for the joint test that all pre-period coefficients equal zero. Controls and FE as in Table 7. Two-way clustered SEs (firm and year) in parentheses.

Table 14: Robustness: Functional Form, Shock Timing, and Investor Fixed Effects

	(1)	(2)	(3)	(4)
Dep. Var.:		$\mathbb{1}$(Debt Deal)		
Specification:	$\ln(1 - \text{MktSim})$	2017 Shock	2017 × MktSim_z	Lead Inv. FE
Post×Treated	0.0022	−0.0151***	−0.0265***	−0.0141*
	(0.0068)	(0.0027)	(0.0024)	(0.0078)
PxTreated×MktSim_z			−0.0181***	−0.0184***
			(0.0038)	(0.0061)
PxTreated× $\ln(1 - \text{Mkt})$	0.2398***			
	(0.0765)			
MktSim_z level			0.0165*	0.0221*
			(0.0098)	(0.0116)
IMR_pharma	−0.0097	−0.0100	−0.0095	−0.0153
	(0.0123)	(0.0123)	(0.0124)	(0.0140)
Controls	Yes	Yes	Yes	Yes
Year, State FE	Yes	Yes	Yes	Yes
Lead Investor FE	No	No	No	Yes
N	15,244	15,244	15,244	15,244
R^2	0.0437	0.0419	0.0428	0.1371

Notes: Column (1) replaces MktSim_z with $\ln(1 - \text{MktSim})$ as an alternative functional form. Columns (2)–(3) use the 2017 enforcement date as the shock. Column (4) adds lead investor fixed effects to the baseline MktSim_z specification; the increase in R^2 from 0.044 to 0.137 reflects investor-level heterogeneity in debt propensity, but the competition interaction is unchanged. All columns use the same sample and controls as Table 7 unless noted. Two-way clustered SEs (firm and year) in parentheses. Coefficients on controls not reported for brevity.