Financing Risk and Startup Growth*

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Abstract

This paper investigates how financing risk, the forward-looking expectation of limited future funding availability, shapes startup behavior. I develop a model of intertemporal investment under uncertainty and show that financing risk, distinct from traditional financial constraints, distorts investment, growth, and survival. I construct a novel text-based measure of financing risk derived from 4.1 million news articles. Exploiting exogenous variation from macroeconomic uncertainty shocks, I find that among the recently funded startups, financing risk causally reduces innovation, especially resource-intensive, exploratory, and novel types. Financing risk also slows employment growth, weakens product development, and increases failure rates. These findings highlight the broader role of anticipated future funding constraints in shaping startup growth in the absence of current financial constraints.

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1. Introduction

One of the most pressing concerns for startup founders is how to secure funding (Kerr and Nanda, 2011). For many new ventures, especially those pursuing high-growth opportunities, access to external capital is not only a tool for scaling, but also a prerequisite for survival (Puri and Zarutskie, 2012; Kerr, Lerner and Schoar, 2014). This is especially true for venture-backed startups, which rely on staged financing to support their product development, team expansion, and market entry (Gompers, 1995; Bergemann, Hege and Peng, 2009; Davis, Morse and Wang, 2020). Yet these firms face not only exceptionally high failure rates and substantial uncertain outcomes (Hall and Woodward, 2010; Kerr, Nanda and Rhodes-Kropf, 2014), but also operate in an environment where venture capital (VC) availability is volatile (Gompers and Lerner, 2004; Gompers et al., 2008).

Given the inherent uncertainty of early-stage ventures and the volatile nature of capital markets they rely on, startups face persistent uncertainty about future funding availability, which I refer to as *financing risk*. This means that startups with strong potential and recent funding may make conservative decisions, not because of current financial constraints, but because of perceived risk around future financing. Formally, *financing risk* is defined as a startup's belief about the probability that it will be unable to secure sufficient external funding in future rounds. Unlike traditional financial constraints, which are based on current liquidity or borrowing capacity, financing risk is fundamentally forward-looking. It captures expectations about future investor behavior, capital market conditions, and the startup's ability to meet milestones required to unlock follow-on funding.

In this paper, I examine how financing risk shapes startups' behavior and outcomes. I begin by developing a model of intertemporal investment in which startups raise capital in stages and must choose investment strategies under uncertainty about future funding availability. The model shows that among the startups without immediate liquidity constraints, financing risk influences investment intensity, growth trajectories, and the likelihood of failure. To empirically test these predictions, I construct a novel text-based measure of financing risk derived from over 4.1 million news articles. I then exploit exogenous variation in macroeconomic uncertainty shocks to identify the causal effects of financing risk. Focusing on the U.S. VC-backed startups that have recently received external financing, I find that financing risk not only diminishes the quantity and quality of innovation but also disproportionately affects resource-intensive, exploratory, and novel innovations. Startups facing higher financing risk also experience slower employment growth and fewer product milestones, as well as lower successful exits and higher failure rates. These findings highlight the broader role of financing risk as a forward-looking determinant of entrepreneurial behavior in the absence of current financial constraints.

A key distinction in this paper is between financing risk and traditional financial constraints. Much of the existing literature on entrepreneurial finance focuses on current financial constraints, where startups are unable to invest or grow due to a lack of capital today (Hellmann and Puri, 2002; Kerr, Lerner and Schoar, 2014; Krishnan, Nandy and Puri, 2015). In contrast, financing risk is forward-looking, where startups may have sufficient cash on hand but behave conservatively if they anticipate difficulty raising capital in the future. This means that while financial constraints explain inaction due to present scarcity, financing risk explains inaction driven by anticipated scarcity. This distinction is especially important for high-growth startups who rely on a sequence of financing rounds to support their growth (Gompers, 1995).

Studying financing risk presents both empirical and theoretical challenges. Empirically, the primary challenge lies in the lack of data on startups' expected future financial conditions. Ideally, one would observe forward-looking beliefs alongside information on startup operations and capital structure, but such data is rarely available, particularly for early-stage ventures. Most existing datasets capture realized financing outcomes or contemporaneous funding conditions, rather than expectations. Survey-based measures that directly ask founders' beliefs about future capital availability are limited in coverage, infrequent, or nonpublic. As a result, there is no standardized or widely used measure of financing risk, and researchers have little visibility into how concerns about future funding shape startup behavior before constraints materialize.

Theoretically, the predictions regarding the effects of financing risk are ambiguous. On the one hand, financing risk could lead firms to adopt more conservative strategies to preserve resources and ensure survival, such as cutting costs, maintaining liquidity, and delaying investment. This aligns with the real options theory of investment under uncertainty (Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1988; Dixit, 1989). On the other hand, startups may respond to financing risk by increasing risk-taking to signal high-growth potential and attract future investment. These incentives are consistent with signaling models (Spence, 1973), especially in the context of innovative startups with uncertain outcomes and capital-intensive scaling needs.

To formalize the concept of financing risk and clarify its implications, I develop a simple dynamic model of intertemporal investment in the context of staged financing, drawing on insights from real options theory and signaling models. In the model, a startup receives external funding through sequential funding rounds and, at each stage, chooses the riskiness of its investment strategy based on expectations about future capital availability. Continuation beyond each funding stage depends on meeting a threshold valuation in the next round, which in turn depends on both realized outcomes and the (unobserved) willingness of investors to provide follow-on capital. Financing risk arises from the startup's belief that it may fail to raise the necessary capital in the future, even if it performs adequately in the current period. This forward-looking belief distorts strategy choices today, as the startup faces a trade-off between pursuing aggressive, high-upside investments that could boost future valuation, and avoiding downside risk that could affect survival. The model distinguishes this belief-based financing risk from traditional financial constraints, which restrict strategic choices directly through current budget limitations.

The model yields four testable predictions. First, among the startups without immediate liquidity constraints, financing risk discourages investment in high-risk, capital-intensive strategies, leading to more conservative behavior. Second, these strategies reduces expected valuation growth, as firms forego ambitious projects that could raise their value. Third, it also increases the likelihood of failure, because more cautious strategies reduce the probability of reaching valuation thresholds needed for continuation. Finally, when startups are financially constrained, investment decisions are driven primarily by budget constraints, and the effect of financing risk is attenuated. This distinction is critical because financing risk matters most when startups have the flexibility to act on their expectations. These predictions structure the empirical analysis and allow us to isolate the effects of financing risk from standard financial frictions.

I test the model's predictions using a comprehensive panel dataset that brings together startup characteristics, financing histories, and startup-level news coverage. The core sample consists of 148,880 U.S. VC-backed startups from 2000 to 2023, drawn from PitchBook. The database offers detailed information on each startup, including the founding year, financing round, and exit outcomes where applicable. To further enrich this dataset, I integrate employment data from Revelio Labs and trademark and patent data from the United States Patent and Trademark Office (USPTO). To construct the measure of financing risk, I source the full text of over 18 million entrepreneurship-related news articles and wire feeds from 1980 to 2023 through ProQuest, and successfully link 4.1 million articles to 49% of the startups in the sample.

In the second part of this paper, I construct a novel measure of financing risk using natural language processing (NLP) applied to startup-specific news coverage. The core idea is that news articles often contain rich, forward-looking information about a startup's activities, business prospects, and perceived challenges in securing funding. I use these narratives to infer the likelihood that a startup may face difficulties raising external capital in future rounds, which I refer to as financing risk. A key advantage of this measure is its forward-looking perspective and interpretability, where the measure reflects the predicted probability of future funding limitations faced by a startup.

The construction of the measure proceeds in three steps. First, I label a training sample of news articles from the Wall Street Journal (WSJ) using a large language model (GPT), which scores each article based on the degree to which it implies concern about future capital availability. Second, I apply transfer learning by fine-tuning two lightweight supervised classification models on the GPT-labeled articles and scaling it to the broader ProQuest corpus, covering over four million startup-specific articles. This approach ensures broad coverage while remaining computationally efficient. Third, I aggregate the resulting measure at the startup-quarter level, creating a continuous, forward-looking measure that captures perceived financing risk over time and across startups.

To validate the measure, I document several empirical regularities. First, the aggregate index closely tracks major cycles in the VC market, rising during periods of systemic uncertainty such as the Nasdaq crash in 2000 and the global financial crisis in 2008. Second, I examine how financing risk evolves over the startup life cycle. Financing risk is lowest in a startup's earliest quarters when startups are operating on recently raised capital and benefit from investor optimism. Financing risk increases as startups age, reflecting increasing capital demands for startups and the higher expectations from investors. Around funding events, I find that financing risk drops sharply in the quarter of the financing round but returns to pre-funding levels within two quarters, highlighting how quickly forward-looking uncertainty re-emerges. I also uncover a U-shaped pattern in the cross-section: financing risk is highest among the smallest and largest startups, with a dip among mid-sized startups. This pattern suggests that financing risk reflects not only funding history but also the intensity of investor scrutiny as startups scale. Finally, I show that financing risk is predictive of future financing outcomes. Startups with higher financing risk are significantly less likely to raise follow-on funding and raise smaller amounts. Taken together, these patterns confirm that the news-based measure of financing risk is both forward-looking and empirically meaningful.

The last part of this paper focuses on estimating the causal effect of financing risk on startup behavior. To do so, I leverage exogenous variation in macroeconomic uncertainty, following the approach of Bernstein (2015) and Jurado, Ludvigson and Ng (2015). Specifically, I instrument the measure of financing risk with the first principal component of nine aggregate uncertainty shocks from Alfaro, Bloom and Lin (2024), including oil price volatility, exchange rate volatility, and policy uncertainty, interacting with the timing of startup-specific news coverage. This strategy is directly motivated by the model, in which startups form expectations about future funding conditions in response to prevailing macroeconomic uncertainty, even if their fundamentals remain unchanged. By exploiting variation in financing risk that is driven by external macroeconomic shocks and anchored to the timing of observed information, I isolate changes in perceived funding risk that are plausibly exogenous to startup strategy or performance.

I show that the instrument strongly predicts financing risk, with strong first-stage F-statistics consistently above 100. The timing of the instrument is carefully designed to align with the formation of financing risk and precede the measurement of outcomes, mitigating concerns about reverse causality or delayed information responses. To support the exclusion restriction, a placebo test reveals that uncertainty shocks do not affect outcomes before the construction of financing risk. This finding is consistent with the idea that uncertainty shocks affect financing risk only through its contemporaneous influence on financing risk. Furthermore, I control for the first-moment components of macroeconomic variables to ensure that the variation used for identification reflects second-moment uncertainty, not directional changes in fundamentals.

Motivated by the model, the main analysis focuses on a subsample of startups that received external financing within the past six quarters. These startups are less likely to face immediate liquidity constraints but remain exposed to forward-looking uncertainty about future funding. Importantly, these recently funded startups are expected to be in a position to make growth-maximizing decisions by allocating capital toward innovation, expansion, and product development. If financing risk distorts their behavior, it signals not only inefficiencies in how startups respond to expectations but also potential misallocation of capital that has already been deployed.

Using the instrumental variables approach, the first empirical results show that higher financing risk significantly reduces both the quantity and quality of innovation. A 0.1 increase in financing risk, interpreted as a 10 percentage point higher probability of future funding limitations, leads to an 8% decline in the number of patents and a 9.8% decline in total citations. Beyond this overall reduction, financing risk disproportionately affects the type of innovation pursued. I find that product innovation is more sensitive to financing risk than process innovation. This is consistent with the notion that product innovation requires more resources and involves greater risk, and process innovation is often complementary to existing investments (Berndt, 1990; Kogan, Papanikolaou and Stoffman, 2020; Bena and Simintzi, 2024). Financing risk is especially detrimental to high-originality and exploratory patents, as measured by Trajtenberg, Henderson and Jaffe (1997) and Custódio, Ferreira and Matos (2019), suggesting that startups scale back from novel technological combinations when future funding is uncertain. Lastly, consistent with the idea that breakthrough innovations are particularly risky and capital-intensive (Kerr and Nanda, 2015; Nanda and Rhodes-Kropf, 2013), I find that the decline in innovation is primarily driven by a drop in breakthrough patents, as measured by Kelly et al. (2021). Together, the first key results show that financing risk affects not only how much startups innovate, but also what kinds of innovation they are willing to pursue by discouraging transformative, high-upside projects in favor of safer, incremental efforts.

The second key result focuses on startup growth and milestone attainment. I find that startups exposed to 0.1 greater financing risk exhibit significantly 19.9% slower employment growth and file 9.2% fewer new product trademarks as an indicator of commercial progress and milestone attainment. These patterns are consistent with a strategic response to anticipated funding limitations that startups reduce hiring and delay product development, even when they are not currently capital-constrained.

The third result is on startup exit and survival. Startups facing higher financing risk are significantly less likely to exit successfully via IPO or acquisition and more likely to fail. A 0.1 increase in the probability of financing risk raises the likelihood of failure by 0.55 percentage points, nearly three times the baseline quarterly failure rate. These findings highlight how financing risk can shape the path-dependent evolution of startups, limiting access to favorable exits and increasing the downside risk.

The last result distinguishes between startups that are currently financially constrained and those that are not. Among startups that have not recently received external financing, I find that the effect of financing risk on most outcomes, such as innovation, product development, and exit, is attenuated. This pattern is consistent with the model's prediction that current financial constraints dominate the expectations about future funding conditions when startups are budget-constrained. However, I still find that employment and bankruptcy remain sensitive to financing risk, even among constrained startups. This suggests that perceived financing risk may amplify the effects of financial constraints, pushing vulnerable firms closer to the margin of failure.

I further explore how the effects of financing risk vary across startups. I find that late-stage and larger startups, those closer to exit and with more established operations, exhibit stronger responses to financing risk in innovation, growth, and exit outcomes. These startups are more exposed to investor expectations and more reliant on continued access to external capital. In contrast, early-stage and smaller startups show weaker effects, except for employment which remains highly responsive to both current and anticipated funding conditions. These patterns highlight that the real effects of financing risk depend not only on startup-level exposure, but also on how closely a startup is tied to investor expectations, capital intensity, and its stage in the venture lifecycle.

I conduct several robustness checks. First, I show that the main findings hold when narrowing the post-financing window to two or four quarters, suggesting that the main findings are not sensitive to the specific window chosen. Second, I address potential sample selection bias in news coverage using inverse probability weighting following Wooldridge (2002, 2007). Third, I control for additional startup-level text-based measures, including a quality risk score constructed using a similar procedure as the financing risk measure, as well as sentiment measures from Loughran and McDonald (2011) and Garcia, Hu and Rohrer (2023). Across all robustness exercises, the core results remain statistically and economically robust.

Related Literature This paper relates to several strands of literature. First, this paper builds on the extensive research on the financing environment and startup outcomes (Kortum and Lerner, 2000; Lerner, Sorensen and Strömberg, 2011; Puri and Zarutskie, 2012; Bernstein, Giroud and Townsend, 2016), which highlights that financial constraints are crucial in shaping startups' outcomes (Hellmann and Puri, 2002; Kerr, Lerner and Schoar, 2014; Krishnan, Nandy and Puri, 2015). In addition to reducing frictions in the availability of capital for new ventures, investment cycles also play an important role in influencing startups' growth and innovation (Gompers and Lerner, 2001, 2004; Gompers et al., 2008; Nanda and Rhodes-Kropf, 2013; Howell et al., 2020). This paper complements this literature by introducing and quantifying a distinct mechanism—financing risk, or the forward-looking belief that future funding may be limited—even in the absence of current capital constraints. I show that this belief-based uncertainty independently distorts startup decisions, even for recently funded firms. This adds a new layer to existing evidence on how VC investment cycles and capital market fluctuations shape entrepreneurial activity.

Second, this paper is also related to the literature on the intertemporal implications of financing constraints (Smith and Stulz, 1985; Thakor, 1990; Froot, Scharfstein and Stein, 1993; Kim, Mauer and Sherman, 1998; Froot and Stein, 1998; Boyle and Guthrie, 2003; Hennessy, Levy and Whited, 2007; Almeida, Campello and Weisbach, 2011). In particular, Almeida, Campello and Weisbach (2011) presents a model in which future financing constraints lead startups to have a preference for investments with shorter payback periods, lower risk, and more liquid, safer assets. Relatedly, this paper connects to the real options theory of investment under uncertainty (Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1988; Dixit, 1989; Gilchrist, Sim and Zakrajšek, 2014; Arellano, Bai and Kehoe, 2019; Alfaro, Bloom and Lin, 2024). My model formalizes this insight in the context of startups and staged VC financing, and the empirical analysis uses a novel, firm-specific, forward-looking measure of financing risk to directly test how expectations of future financing constraints drive strategic inaction in high-growth entrepreneurial settings.

Third, this paper is also related to a small literature on intertemporal coordination problems in investment. Financing risk is conceptually similar to the rollover risk problem identified in the corporate debt literature. In that context, a startup attempting to issue new bonds to replace maturing ones faces debt costs that reflect not only its own credit risk but also a liquidity premium due to the illiquidity of the secondary debt market (Acharya, Gale and Yorulmazer, 2011; He and Xiong, 2012*a*,*b*; Brunnermeier and Oehmke, 2013). In the context of VC financing, Nanda and Rhodes-Kropf (2017) theoretically shows that an otherwise healthy startup might not be able to raise follow-up capital from other investors due to financing risk. This paper contributes to this literature by providing empirical evidence on the real effects of financing risk in the VC context.

Finally, I contribute to the growing literature that treats entrepreneurship as experimentation (Kerr, Nanda and Rhodes-Kropf, 2014; Gans, Stern and Wu, 2019; Camuffo et al., 2020; Agrawal, Gans and Stern, 2021; Camuffo et al., 2022; Bolton et al., 2024). Financing risk, as a representative of continuation features, is one of the key frictions in the experimentation process that determines the extent to which experimentation can be pursued (Kerr, Nanda and Rhodes-Kropf, 2014). Existing empirical research on financing risk for startups focuses on how startups can mitigate financing risk associated with boom and bust cycles in the availability of finance (Nanda and Rhodes-Kropf, 2013; Howell et al., 2020) and a vibrant market for ideas for startups to license or sell their technology if it is doing well (Gans, Hsu and Stern, 2002). I build on this by constructing a startup-specific measure of financing risk and showing how this belief-based risk distorts innovation direction, milestone attainment, and exit probabilities.

2. A Model of Intertemporal Investment Decisions

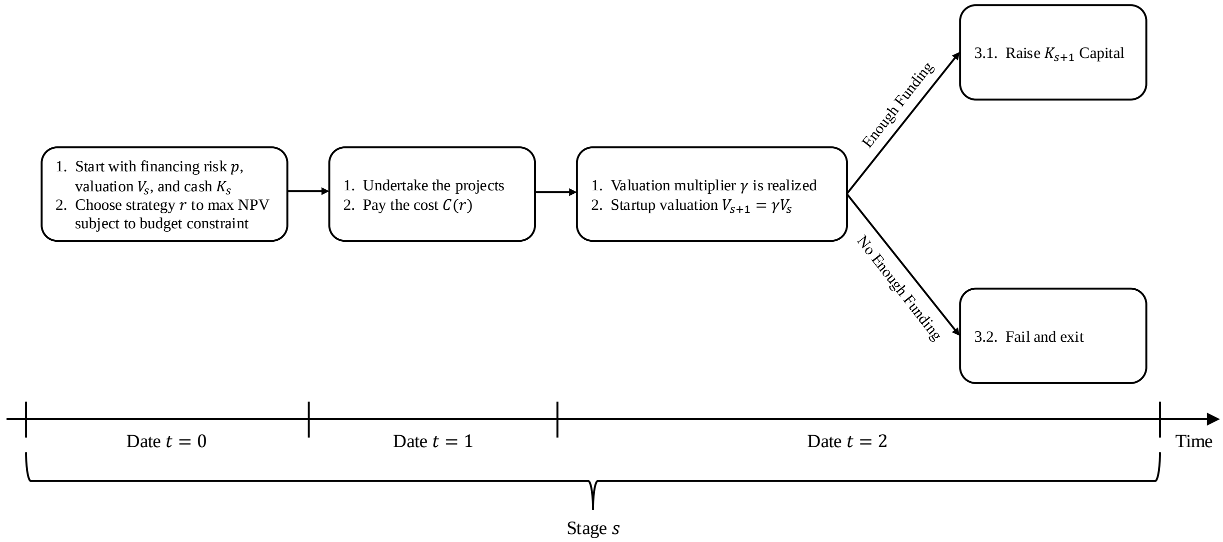
The survey-based evidence in Appendix A.1 demonstrates that startups adjust their behavior in response to anticipated funding conditions.[1] However, it is not immediately obvious why such adjustments occur, particularly among firms that are not subject to current financial constraints.

To clarify the underlying mechanism and to distinguish financing risk from current financial constraints, I present a simple model of intertemporal investment decisions that isolates the effect of financing risk, the forward-looking uncertainty about raising sufficient capital in the next funding round. The model is built around three core features of startup financing. First, in staged financing, additional funding in the next round is required for continuation, where investors can stage their investments and learn more about the startup's potential (Gompers, 1995; Bergemann, Hege and Peng, 2009; Davis, Morse and Wang, 2020). Second, startups can adjust their strategy and achieve milestones to signal high-growth potential and attract future investments (Hsu, 2006; Bienz and Hirsch, 2012; Ozmel, Robinson and Stuart, 2013). Third, startups anticipate the availability of future funding and adjust their investment decisions today (Boyle and Guthrie, 2003; Hennessy, Levy and Whited, 2007; Almeida, Campello and Weisbach, 2011).

This framework allows us to distinguish the role of financing risk from traditional financial frictions and to derive testable predictions about how financing risk shapes startup behavior, including investment behavior, startup growth, and the likelihood of failure.

[1] I provide supporting survey evidence in Appendix A.1 using the Survey on the Access to Finance of Enterprises (SAFE), which includes firm-level expectations of future financing conditions. I show that firms anticipating limited future funding systematically adopt more conservative growth and innovation strategies, even when they are not currently financially constrained. These findings highlight the forward-looking nature of financing risk and motivate a theoretical framework in which firms' strategic decisions are shaped by the anticipation of future capital availability.

Figure 1. Timeline of The Model



Notes. This figure presents the timeline of our model in a single financing interval at stage s. It has three dates: $t = 0$, $t = 1$, and $t = 2$. At date $t = 0$, the startup forms the belief about financing risk p, and has the valuation V_s and cash K_s. The startup needs to decide the strategy riskiness r to maximize its expected NPV, subject to budget constraints. At date $t = 1$, the startup undertakes the operations and projects determined by r, and pays the cost $C(r)$. At date $t = 2$, the random valuation multiplier γ realizes and the startup receives the valuation $V_{s+1} = \gamma V_s$. If there is sufficient funding provided by investors, the startup will raise K_{s+1} capital and continue to operate. Otherwise, it will exit the market.

2.1. Setup: Startup Valuation and Timeline

I model a startup progressing through a sequence of financing stages $s \in \{1, \ldots, N\}$, and focus on a single financing interval within one such stage. At each stage, the startup must raise capital from external investors to continue operations, such as hiring, conducting R&D, or product delivery. The required capital at each stage, $\{K_1, \ldots, K_s, K_{s+1}, \ldots, K_N\}$, is taken as exogenous and reflects the startup's industry and business model. The startup owns an intangible asset, which determines its valuation V_s at stage s. This reflects the nature of early-stage ventures where their valuations come from intangible potential in the form of early technologies or product pipelines in the absence of cash flow.

The model spans three dates within a single financing interval: $t = 0$, $t = 1$, and $t = 2$, capturing the dynamics of staged financing. Startups raise just enough capital to reach a milestone and then reply on follow-on funding to proceed to the next stage. Figure 1 summarizes this timeline.

At date $t = 0$, the startup begins with valuation V_s and cash K_s at the start of stage s. It chooses an investment strategy with riskiness r, which governs how aggressively the startup pursues growth through R&D, product development, or market expansion. A higher r represents more ambitious or resource-intensive initiatives, which carry greater upside potential but also more downside risk.

At $t = 1$, the startup implements the strategy and incurs a cost of $C(r)$. This cost represents the burn rate associated with different strategies. For simplicity, I assume the cost takes a linear form, $C(r) = C_0 + C_1 r$, where C_0 is the fixed cost and C_1 is the marginal cost of additional risk. This cost must not exceed the startup's cash K_s, imposing the budget constraint $C(r) \leq K_s$. To keep the model tractable, I assume no new information or signals arrive at this stage, although this could be relaxed in future extensions.

At date $t = 2$, the outcome of the startup's strategy is realized. Specifically, a random multiplier γ is drawn, which transforms the current value into a new valuation:

$$V_{s+1} = \gamma V_s. \tag{1}$$

The distribution of γ depends on the startup's investment strategy r, reflecting how risk shapes future outcomes. Specifically, I assume that γ follows a uniform distribution:

$$\gamma \sim \text{Uniform}(\gamma_0 - r^{\beta}, \gamma_0 + \alpha r^{\beta}), \tag{2}$$

where $\gamma_0 \geq 1$ is the baseline multiplier for a conservative strategy (i.e., $r = 0$); $0 < \alpha \leq 1$ captures the upside expansion from risk; and $0 < \beta < 1$ governs the scale of downside exposure. This structure captures the intuition that riskier strategies lead to higher variance—greater breakthrough potential, but also a greater likelihood of failure.

Continuation depends on the startup's ability to raise the next round of capital. Let $K_{s+1}^{\max} = \lambda_{s+1}^{\max} V_{s+1}$ be the maximum amount investors are willing to provide at stage $s + 1$, where $0 \leq \lambda_{s+1}^{\max} \leq 1$ is the share of valuation fundable in that round. I assume that $\lambda_{s+1}^{\max}$ is exogenous and varies across stages. If $K_{s+1} \leq K_{s+1}^{\max}$, the startup receives funding and proceeds. Otherwise, it exits without any liquidation value. Then the probability of continuation is:

$$Pr\left(K_{s+1}^{max} \geq K_{s+1}\right) = \Pr\left(\gamma \geq \gamma_{s+1}^{min}\right) = \frac{\alpha}{1+\alpha} - \frac{\gamma_{s+1}^{min} - \gamma_0}{(1+\alpha)r^{\beta}}, \tag{3}$$

where $\gamma_{s+1}^{min} = \frac{K_{s+1}}{\lambda_{s+1}^{max} V_s}$ is the minimum valuation multiplier required to raise K_{s+1}. I assume $\gamma_{s+1}^{min} \geq \gamma_0$ to ensure that the startup may have an incentive to choose a nonzero risk level. If raising capital is trivially easy, the optimal strategy is simply to pick $r = 0$.

2.2. Financing Risk

A core feature of staged financing is the ongoing need for startups to secure follow-on capital to reach the next development milestone. This introduces uncertainty even when the starup currently holds sufficient funding. We define this forward-looking concern—the possibility of failing to raise enough capital in future rounds—as financing risk. Importantly, a startup may not be financially constrained today but still alters its behavior in anticipation of future shortfalls. The key insight is that concern about capital access arises not from a current shortage, but from the unknown conditions at the next funding round.

To formalize this idea, suppose the maximum capital investors are willing to provide at the next stage, $K_{s+1}^{\max}$, is unobservable to the startup and privately known to investors. Equivalently, the startup is uncertain about the minimum valuation multiplier $\gamma_{s+1}^{\min}$ required to raise K_{s+1}. Let p denote the startup's belief about the probability of failing to meet this unknown threshold at the beginning of stage s $(t = 0)$. The financing risk p is defined as:

$$p = \Pr\left(\gamma < \mathbb{E}_0[\gamma_{s+1}^{min}] \mid \gamma \geq \gamma_0\right), \tag{4}$$

where $\mathbb{E}_0[\gamma_{s+1}^{min}]$ is the startup's belief about the required valuation multiplier to secure follow-on funding.[2] We focus on the cases where the startup has achieved the minimal acceptable performance (i.e., $\gamma \geq \gamma_0$) but yet still faces the risk of not meeting the unobserved requirements by investors. If γ is less than γ_0, the startup is effectively non-viable

[2] Under the assumption that γ follows a uniform distribution with support determined by strategy r, this belief maps into financing risk as:

$$\mathbb{E}_0[\gamma_{s+1}^{min}] = p\alpha r^{\beta} + \gamma_0.$$

and its concern vanishes.

This definition of financing risk highlights that financing risk depends on two forces: the distribution of future valuations that are governed by strategy choice r and the startup's belief about investors' requirements $\mathbb{E}_0[\gamma_{s+1}^{\min}]$. A more aggressive strategy increases the dispersion of possible outcomes, improving the chance of exceeding the required threshold but also raising downside risk. A conservative strategy narrows this distribution, making it less likely to exceed investor expectations.

Although I treat $\mathbb{E}_0[\gamma_{s+1}^{\min}]$ as exogenous in the model, in practice it is shaped by both startup-specific and macroeconomic factors. Strong fundamentals, such as a capable founding team or a compelling product, can improve investor confidence, reducing the threshold required for funding. Conversely, during downturns or when venture capital liquidity is low, investors demand more validation before committing capital, raising $\mathbb{E}_0[\gamma_{s+1}^{\min}]$ and hence the financing risk. Thus, shifts in either startup quality or macroeconomic conditions can alter financing risk, even holding current liquidity constant. In Section 4, I exploit exogenous variation in aggregate market conditions to identify the causal effect of financing risk on startup behavior.

In sum, financing risk captures a startup's forward-looking concern about capital access. Even in the absence of immediate financial constraints, startups may scale back investment if they anticipate difficulty raising funds in the future.

2.3. Startup Optimal Decision

At date $t = 0$, the startup chooses the riskiness level of its strategy r to maximize expected net present value (NPV), given by the difference between the expected payoff $E_0[V_{s+1}]$ and the cost of implementing the strategy $C(r)$:

$$\Pi_s(r) = \underbrace{\Pr(\gamma \geq \mathbb{E}_0[\gamma_{s+1}^{min}]) \times \mathbb{E}_0[V_{s+1} \mid \gamma \geq \mathbb{E}_0[\gamma_{s+1}^{min}]]}_{= \text{ expected payoff } E_0[V_{s+1}]} - \underbrace{(C_0 + C_1 r),}_{= \text{ cost } C(r)} \tag{5}$$

subject to the budget constraint:

$$C_0 + C_1 r \leq K_s. \tag{6}$$

This setup reflects a fundamental trade-off that pursuing a riskier strategy (higher r) can increase expected valuation through higher upside but also raises the probability of failure, especially under high financing risk. This trade-off echoes classic signaling models (Spence, 1973) and real options theories of investment under uncertainty (Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1988; Dixit, 1989).

Assuming an interior solution and no binding liquidity constraint, the startup chooses r such that the marginal benefit equals the marginal cost. Under the uniform distribution of γ in Equation (2), the expected continuation valuation becomes:

$$E_0[V_{s+1}] = \frac{\alpha}{1+\alpha}\left((1-p)\gamma_0 + \frac{1-p^2}{2}\alpha r^{\beta}\right)V_s. \tag{7}$$

Substituting into Equation (5) and solving the first-order condition yields the unconstrained optimal riskiness level r^U:

$$r^U = \left(\frac{(1-p^2)\alpha^2\beta V_s}{2(1+\alpha)C_1}\right)^{\frac{1}{1-\beta}}, \tag{8}$$

This expression reveals how financing risk p directly shapes the startup's optimal investment strategy. A higher p reduces the perceived benefits of risk-taking by increasing the likelihood that the startup fails to secure future funding, even conditional on a strong realized valuation. Hence, financing risk discourages aggressive strategies, pushing startups to preserve resources and ensure survival, regardless of current financial constraints.

If the optimal choice violates the budget constraint, the startup selects the constrained maximum level r^C:

$$r^C = \frac{K_s - C_0}{C_1}. \tag{9}$$

Now we can state the startup's overall optimal strategy decision as follows.

Lemma 1 (Optimal Investment Strategy). *Given the startup's problem in Equation (5) and budget constraint in Equation (6), the optimal riskiness level r^* is given by:*

$$r^* = \min(r^U, r^C), \tag{10}$$

where r^U is given by Equation (8) and r^C is given by Equation (9).

Lemma (1) illustrates the distinction between two key financial frictions: current financial constraints and forward-looking financing risk. While the financial constraint directly caps the feasible strategy through the budget constraint, the financing risk reduces the return to risk-taking by lowering the probability of successful continuation. Importantly, even when a startup has sufficient cash to implement any strategy (i.e., $r^U \le r^C$ for all $p \in [0,1]$), the financing risk still distorts the startup's incentives to take the risk.

To isolate the role of financing risk, I focus on the unconstrained case where the startup can always afford the optimal strategy, i.e., $r^U \le r^C$. This holds when:

$$C_0 + C_1 \left(r^U|_{p=0}\right) = C_0 + C_1 \left(\frac{\alpha^2 \beta V_s}{2(1+\alpha)C_1}\right)^{\frac{1}{1-\beta}} \le K_s. \tag{11}$$

In this case, the startup will always choose the riskiness level r^U that maximizes its expected NPV, and the only distortion comes from financing risk.

Next, I present three key propositions that characterize how financing risk p influences startup behavior, growth, and failure rate.

Proposition 1 (Optimal Strategy and Financing Risk)**.** *Suppose the startup is unconstrained given by Equation (11). The derivative of the optimal riskiness level r^* with respect to the financing risk p is given by:*

$$\frac{\partial r^*}{\partial p} = \frac{\partial r^U}{\partial p} = -\frac{2p}{1-p^2}\frac{1}{1-\beta} r^U < 0. \tag{12}$$

That is, the optimal riskiness level r^* declines with financing risk p.

As financing risk increases, the startup optimally adopts a more conservative strategy to hedge against the increased probability of failure in the next funding round.

Proposition 2 (Valuation Growth and Financing Risk)**.** *Suppose the startup is unconstrained given by Equation (11). The derivative of the valuation growth rate $g^* = \frac{E_0[V_{s+1}]}{V_s} - 1$ with respect to the financing risk p is given by:*

$$\frac{\partial g^*}{\partial p} = -\frac{\alpha}{1+\alpha}\left(\gamma_0 + p\frac{\alpha}{1-\beta}(r^U)^{\beta}\right) < 0. \tag{13}$$

That is, the valuation growth rate g^* declines with financing risk p.

This proposition shows that financing risk not only discourages risk-taking but also depresses expected valuation growth, even in the absence of binding cash constraints.

The last proposition shows the relationship between financing risk and failure rate.

Proposition 3 (Failure Rate and Financing Risk)**.** *Suppose the startup is unconstrained given by Equation (11). The derivative of the failure rate $f^* = \Pr(\gamma < \gamma_{s+1}^{min})$ with respect to the financing risk p is given by:*

$$\frac{\partial f^*}{\partial p} = \frac{\gamma_{s+1}^{min} - \gamma_0}{1+\alpha} \frac{2p}{1-p^2} \frac{\beta}{1-\beta} (r^U)^{-\beta} > 0. \tag{14}$$

That is, the failure rate f^* increases with financing risk p.

As in Equation (3), the continuation probability of a startup is determined by the minimum valuation multiplier γ_{s+1}^{min} that is only observed by the investors. However, financing risk p will still indirectly affect a startup's failure risk, not because of changes in investor behavior, but because it prompts startups to pursue less ambitious strategies that are less likely to yield valuations high enough to qualify for future funding.

2.4. Hypotheses

The model presented above yields a set of testable implications that guide the empirical analysis. These predictions highlight how financing risk, distincting from immediate financial constraints, can shape startup decisions in forward-looking ways.

In particular, our focus is on startups that are not currently financially constrained. These startups have sufficient liquidity to pursue a range of strategic options, yet may still behave conservatively due to concerns about the availability of capital in future rounds. This distinction allows us to isolate the role of financing risk from the standard friction of financial constraints.

First, in Proposition (1), the model shows that financing risk dampens a startup's incentives to pursue ambitious and high-upside strategies. Even if such strategies increase the probability of failing to secure future funding, the downside risk reduces their attractiveness. As a result, startups facing higher financing risk will choose more conservative, less resource-intensive paths. This leads to the first empirical hypothesis:

Hypothesis 1. *Among startups that are not currently financially constrained, higher financing risk is associated with more conservative and less resource-intensive investment strategies.*

Second, as shown in Proposition (2), the model predicts that these conservative choices translate directly into lower expected valuation growth. Startups that scale back investment intensity due to financing risk generate smaller expected gains in future valuation, even if they avoid downsizing. This gives rise to the second hypothesis:

Hypothesis 2. *Among startups that are not currently financially constrained, higher financing risk is associated with a lower growth rate in valuation.*

Third, Proposition (3) shows that financing risk also increases the likelihood of failure. When startups anticipate difficult funding conditions, they are more likely to choose strategies that fail to generate sufficiently high valuations to meet unobserved investor thresholds. Hence, financing risk indirectly raises the probability of exit:

Hypothesis 3. *Among startups that are not currently financially constrained, higher financing risk is associated with a higher failure rate.*

Finally, the model also predicts that the effect of financing risk depends on a startup's current financial position. As shown in Lemma 1, when a startup is financially constrained, i.e., when its current budget limits strategic choices, its optimal strategy becomes insensitive to financing risk. In such cases, it is the current financial constraints instead of future expectations that determine decision-making. This leads to a fourth testable implication:

Hypothesis 4. *The effect of financing risk on startup behavior is attenuated when the startup is currently financially constrained.*

Together, these four predictions form a coherent empirical framework. When current liquidity is not a binding constraint, startups may adjust their behavior in response to forward-looking financing risk. Conversely, when financial constraints are binding, financing risk plays a reduced role. I will test these hypotheses using a large dataset of U.S.

VC-backed startups, focusing on how startup's expectations about future funding availability affect their investment behavior, growth outcomes, and survival rate.

3. Data and Measurement

The main objective in this section is to obtain the measure of financing risk for U.S. VC-backed startups. To do so, I combine data from multiple sources. I begin by compiling a comprehensive sample of U.S. VC-backed startups and their financing activities from Pitchbook, supplemented with employment data from Revelio Labs and innovation and trademark data from USPTO. I also collect news articles related to entrepreneurship from ProQuest and use these articles to construct our financing risk measure. Below, I first describe data collection. Then, I discuss the construction of the financing risk measure, its properties, and economic interpretation.

3.1. Data

Startup Data The primary source of data on U.S. VC-backed startups for this paper is Pitchbook, which is one of the leading databases for venture capital investment. Pitchbook gathers data from various sources, including regular filings (e.g., SEC Form D filings), contacts with funds and portfolio firms, and news articles. It has been utilized by the National Venture Capital Association, the US National Science Board, and others. This study focuses on U.S. startups from Pitchbook that received venture capital funding between 2000 and 2023, with deals categorized as all VC stages,[3] and marked as "Completed". This gives us a sample of 148,880 U.S. VC-backed startups from 41 broader industry groups and 219 detailed industries.[4] While the coverage of Pitchbook before 2000 is spotty, PitchBook made considerable efforts to backfill earlier years in the 2000s (Lerner et al., 2024). I extract the company-level information on name, founding year, location, industry, website, and LinkedIn URL. PitchBook also tracks startups and contains the events to indicate

[3] I consider all venture capital stages, including "Pre/Accelerator/Incubator", "Angel", "Seed", "Early Stage VC", and "Later Stage VC", and "Other Stages", as classified by PitchBook.

[4] The industry classification is refined by PitchBook to adopt the real activities of startups that operate in the same general space, including 7 industry sectors, 41 industry groups, and 219 detailed industries. Table A.2 provides the number of startups across 41 industry groups in our sample.

outcomes, including whether a startup is bankrupt, acquired, or went public. For each financing deal, I extract the information on the deal date, amount, number of investors, and number of new investors.

I supplement the startup data with the employment information from Revelio Labs. Revelio Labs is a comprehensive workforce dynamics dataset containing individual-level employment profiles from Linkedin, including company names and starting and ending dates. This dataset offers broad coverage in the U.S., especially for private firms (Babina et al., 2024). I link the two datasets using the LinkedIn URL provided by Pitchbook and Revelio Labs. For the rest of the startups, I use a fuzzy matching method based on company names, basic identity information, and location, similar to Howell et al. (2020). This matching results in good coverage of the sample—79% of the startup sample in Pitchbook has employment data from Revelio Labs.

To obtain the innovation profile of a startup, I obtain the patent data from the United States Patent and Trademark Office (USPTO), covering eight million patents granted by the USPTO from 1976 to 2023.[5] The information for each patent includes the application and grant date, the technology classification based on the Cooperative Patent Classification (CPC) system, and the assignee information, including the name and the location of the assignee. Following Kogan et al. (2021), I use citation-weighted patent count to measure the general quality of a patent, defined as the number of citations received by the patent, scaled by the average number of citations from its own vintage and technology class. As above, the patent data is merged with PitchBook data following a fuzzy matching procedure, which covers 14% of the startups in the PitchBook sample.

To further capture different characteristics of startups' innovation profiles about riskiness and resource intensity, I also compute various patent measures. To capture the type of patent on whether it is serving for product or process innovation, I categorize a patent into product and process patent based on the textual component in the claims, and I follow Bena and Simintzi (2024) for construction. As suggested by Trajtenberg, Henderson and Jaffe (1997), I compute the originality measure to proxy the extent to which a patent uses knowledge from a wide range of fields. As proposed by Manso (2011) and further

[5]I access the patent data from the USPTO PatentsView platform through `https://patentsview.org`.

extended by Almeida, Hsu and Li (2013) and Custódio, Ferreira and Matos (2019), explorative measures the intensity with which a firm innovates based on knowledge that is new to the firm, and it is computed as the share of citations that doesn't refer to existing knowledge, which includes all the patents that the firm invented and all the patents that were cited by the firm's patents filed over the past five years. Finally, to identify whether a patent is a breakthrough patent, I use the definition of importance measure in terms of its novelty and impact from Kelly et al. (2021) (KPST).[6]

While the patent data provides a comprehensive view of a startup's innovation profile, it may not capture all aspects of other innovative activities, such as the role of trademarks in distinguishing products and creating customer loyalty. To address this limitation, I supplement the startup data with trademark data from the USPTO, containing seven million trademarks registered by the USPTO from 1870 to 2023.[7] This dataset includes information on the trademark application date and registration date, and trademark owners. I merge the trademark data with the startup data using a similar matching procedure, resulting in 36% of the startups in the Pitchbook sample having trademark data.

News Data The measure of financing risk is constructed using the full text of news articles. I obtained the raw text and metadata of a large sample of news articles from ProQuest. News articles have been widely used in the literature to study various aspects of financial market and macroeconomics (Baker, Bloom and Davis, 2016; Bybee et al., 2021; Goetzmann, Kim and Shiller, 2022). The ProQuest news databases that I use cover a wide range of topics with a strong focus on business and finance. Meanwhile, most news articles about startups include the background of the startup, its business and activities, and a short interview with the founders or CEOs. Therefore, it is a natural choice as a source of information on which I can assess the forecast about future funding availability for the startups.

The news data from ProQuest used in this paper contains three complementary news

[6] This patent-level importance measure can be accessed at https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Extended-Data.

[7] The USPTO trademark data can be accessed at https://developer.uspto.gov/product/trademark-case-file-economics-data-stata-dta-and-ms-excel-csv.

databases, including ProQuest ABI/Inform Collection, U.S. Newsstream Database and European Newsstream Database.[8] ProQuest ABI/Inform Collection covers 258 million news and popular press articles as well as journal articles on business subjects from 1971 to 2023. U.S. Newsstream Database contains 217 million news articles from national and local newspapers in the U.S. and European Newsstream Database contains 105 million news articles from local newspapers in European countries from 1980 to 2023. To further narrow down the news articles that are related to entrepreneurship, I restrict the sample with source types from "Newspapers", "Wire Feeds", "Blogs, Podcasts, & Websites", and "Trade Journals", and search for articles with at least one word on venture capital, private equity, entrepreneur, entrepreneurship, entrepreneurial, or startup. This leaves us with a total sample of 18.6 million news articles. For each news article, I observe the metadata on the publication date, source type, and journal name, as well as the raw text, including the title, abstract, and full text. For 71.9% of the news sample, ProQuest provides the names of the companies associated with the news.[9] For the rest of the news articles (25.8%), I extract the names of companies from the title and abstract using the named entity recognition (NER) model from spaCy.[10] Using the name fuzzy matching procedure, I can link 4.1 million news articles to the startups from PitchBook.[11] 49% (73,290) of the PitchBook startups are mentioned at least once in the news articles.

While the raw text data from ProQuest is subject to the terms of use within the TDM Studio,[12] I manually collect a sample of news articles from WSJ to construct the financing risk measure using GPT. As a leading financial publication, WSJ is widely regarded as a reliable source of information on business and finance (Bybee, 2023). I collect 39,728 news

[8]We access the news articles from ProQuest through the TDM Studio at https://tdmstudio.proquest.com/home. The details of the ProQuest ABI/Inform Collection, U.S. Newsstream Database, and European Newsstream Database are available at https://www.proquest.com/abicomplete, https://www.proquest.com/usnews, and https://www.proquest.com/europeannews, respectively.

[9]ProQuest identifies the name of companies associated with the news articles through an automated system as well as editorial work.

[10]The spaCy model can be accessed at https://spacy.io/models/en. An entity is identified as a company if its label is "ORG".

[11]Figure A.1 presents the number of news articles with entrepreneurship-related keywords and matched to PitchBook startup over time. Appendix Table A.3 provides a list of the top 30 journals from the matched PitchBook Sample.

[12]The Supplemental Terms of Use of TDM Studio says that "Notwithstanding the general prohibition on text and data mining under the Terms and Conditions, Authorized Users are expressly allowed within the designated TDM Studio Workbench to create derived data from the textual content of the eligible databases."

articles from WSJ between 1984 to 2022. As before, these articles are required to contain at least one word on venture capital, private equity, entrepreneur, entrepreneurship, entrepreneurial, or startup. This sample of news articles is used to construct the measure of financing risk from GPT and then applied to the broader sample of news articles from ProQuest using transfer learning.

3.2. Measuring Financing Risk

3.2.1. Conceptual Intuition

The measure of financing risk is designed to capture a startup's forward-looking expectation about the availability of future funding. As formalized in Equation (4), financing risk is defined as the probability that a startup will be unable to raise sufficient capital in the next funding round. This probability is shaped by two key components: the startup's underlying fundamentals (such as growth potential and strategy), and its beliefs about investor expectations. The latter is heavily influenced by the inherent uncertainty of external financing, particularly from venture capital markets, where funding decisions are often contingent on shifting market conditions and investor sentiment. Since startups often rely on these external sources to fuel their growth and innovation, perceived financing risk plays a crucial role in shaping their investment decisions.

While financing risk is inherently a subjective belief, it is informed by public signals, many of which are reflected in how startups are described in the media. News articles often convey rich, forward-looking information about a startup's business activities, partnerships, market positioning, and strategic direction. Crucially, they also embed references to broader market conditions, investor outlook, and sector-specific uncertainty. As a result, news coverage provides a natural window into how both startup-level developments and macroeconomic forces shape expectations about future funding. By analyzing these texts, we can infer how market participants perceive the startup's funding prospects, effectively recovering the belief-based financing risk that drives strategic decisions but is rarely observed directly in structured data.

I implement this idea using natural language processing (NLP) methods that classify the content of each article according to the likelihood that it reflects concern over future funding availability. The probabilistic output of the NLP model aligns naturally with the definition of financing risk as a probability measure. Each observation reflects the predicted likelihood that a startup will face difficulty raising capital going forward based on the text. This methodology is especially useful in the startup context, where data is often sparse and traditional financing measures tend to be backward-looking. Our news-based measure offers a timely and forward-looking view of financing conditions, grounded in how market participants interpret and react to startup developments in real-time.

3.2.2. Construction

I construct a startup-quarter-level measure of financing risk using a three-step procedure. First, I label a training sample of news articles using a large language model. Second, I train and apply a transfer learning model of financing to the full sample of news articles from ProQuest. Finally, I aggregate the resulting measure at the startup-quarter level.

Step 1: Label Training Articles Using GPT. To initiate the process, I begin by labeling a training sample of startup-related news articles using a large language model. As discussed earlier, news content often contains rich and forward-looking signals about a startup's financial prospects. I use the Generative Pre-trained Transformer (GPT) model to extract this information. GPT is a type of large language model based on transformers deep learning architecture. It is designed to learn the patterns of language and decode the underlying meaning of the text, using training data from various domains. Given GPT's capacity to understand nuanced language and infer context across various business domains, it is particularly well-suited for our purpose of extracting the forecast of future funding availability for startups from news articles.

I use the GPT-4o mini model provided by OpenAI with a total limit of 16,384 tokens or around 12,000 words.[13] Figure A.3 shows the prompt format used to query GPT. Each query to GPT receives the title, abstract, and full text of the news article, and in response, GPT assesses whether the article provides evidence about the likelihood of future venture funding for the startup. I also provide detailed requirements on what information to

[13] I accessed the GPT-4o mini model through OpenAI API at the end of August 2024, which is the 2024-07-18 version of the model.

extract from the news article, focusing exclusively on the information related to the availability of future financing from venture capital and private equity markets and excluding unrelated factors such as macroeconomic commentary or internal operations. GPT returns a score between -1 and 1, with positive values indicating expected funding constraints and negative values suggesting future funding is likely. Articles unrelated to financing availability are assigned a value of "X".

A potential drawback of GPT is its occasional tendency to confidently provide inaccurate information. To ensure consistency, I fixed the random seed and set the temperature to zero. Second, I ask GPT to provide the confidence level of its answer on a scale between 0 and 1, and I retain only articles with confidence scores above 0.5. I also ask GPT to provide an explanation for each answer, which shifts the objective function of GPT from prediction to explanation and allows for manual verification of the reasoning behind the scores. Finally, I query three times for each news article and choose responses that are consistent with the majority. I then take the average of the scores across multiple queries for each news article as the final measure of financing risk.

This procedure yields a high-confidence, labeled dataset of 13,994 news articles from The Wall Street Journal, representing 35.2% of the initial sample. The average resulting score is -0.147, with a standard deviation of 0.861, reflecting a tendency for media coverage to highlight successful, well-funded startups (Barberis, 2018). The sample also shows substantial variation in the financing risk measure. Among these articles, 33.7% indicate constrained future funding (positive values), 53.5% suggest sufficient future funding (negative values), and 12.8% report on financing without a clear signal (scores near zero).

Step 2: Transfer Learning to Full News Corpus. While GPT provides high-quality labels, it is subject to several limitations that make it impractical for large-scale implementation. First, GPT's output is not inherently a calibrated probability, making its interpretation less transparent. Second, the WSJ articles labeled with GPT represent only less than 2% of the Pitchbook sample. Expanding coverage to a wider set of startups would require processing millions of news articles, which is both computationally expensive and time-intensive. Third, the raw text data from ProQuest is subject to the terms of use within the

TDM Studio, meaning that I cannot apply GPT to the ProQuest dataset.

To address these limitations, I adopt a transfer learning strategy. Using the GPT-labeled WSJ articles as training data, I build a lightweight, local model that generalizes the insights extracted by GPT to the broader ProQuest news corpus. This approach enables scalable application while producing a probability-based interpretable measure of financing risk. Specifically, the model outputs the predicted probability that a given news article signals limited future funding, which provides a direct and consistent interpretation of financing risk across startups and time.

I implement this using BERT-Tiny (Turc et al., 2019), the pre-trained miniature version of the Bidirectional Encoder Representations from Transformers (Devlin, 2018, BERT). While standard BERT contains 110 million parameters, BERT-Tiny has just 4 million, making it substantially faster to train and deploy while maintaining strong performance.[14]

I fine-tune two separate and subsequent models. The first is a binary classifier that predicts whether an article discusses the future availability of external funding. I use all WSJ articles for training, assigning a label of 1 to those with GPT-based financing risk scores and 0 to those without.[15] The second model is a three-class classifier trained on the 13,994 GPT-labeled articles to classify articles as indicating constrained (1), neutral (0.5), or sufficient (0) future funding. The out-of-sample classification accuracy is 81.5% for the binary model and 79.8% for the three-class model, reflecting strong predictive performance on unseen data.

I then apply the fine-tuned models to the full set of startup-related articles from ProQuest. The binary classifier identifies 0.49 million articles related to future funding, covering 44,031 unique startups. For these, the three-class model predicts a probability distribution over the three categories. I then compute a probability-weighted average in the range of [0,1] as the final financing risk measure for each article, where higher values indicate a greater likelihood of future funding constraints.

[14] I access and fine-tune the BERT-Tiny model through the Hugging Face Transformers library at https://huggingface.co/google/bert_uncased_L-2_H-128_A-2. The fine-tuned BERT-Tiny models are applied to ProQuest news articles on the TDM Studio, using a virtual machine with 4 CPUs and 16 GB RAM.

[15] Figure A.1 shows the number of news articles that are related to the future funding availability for startups in the VC news sample and startup sample over time, respectively.

Step 3: Aggregate to Startup-Quarter Level. To construct the final panel dataset, I aggregate article-level financing risk scores to the startup-quarter level. For each startup in each quarter, I compute the average score across all relevant articles. The resulting measure reflects the startup's perceived financing risk in that period, grounded in real-time media coverage and conditioned on startup-specific events and market sentiment.

This measure captures heterogeneity across startups within the same industry and period, leveraging narratives at the startup level rather than broad sectoral trends. Because the measure is built on probabilistic outputs from language models, its interpretation is straightforward: a higher value indicates a higher predicted probability that a startup will face difficulty accessing external funding shortly. By combining natural language processing with large-scale media data, the measure offers a forward-looking, interpretable, and scalable proxy for financing risk, which addresses the limitations of traditional, backward-looking financing indicators.

3.2.3. Discussions on The Measurement

Selection Into News Mentions The availability of our measure is limited to the startups that are mentioned in the news articles. To assess potential selection bias, I compare observable characteristics across startup-quarter observations with and without venture-related news coverage, as well as whether the mentions are related to future funding. Table A.4 presents these comparisons. Startups mentioned in the news tend to be older, more mature, receive more VC funding from more investors, and are more likely to exit via IPO or acquisition. These patterns are stronger for startups featured in financing-related news, consistent with the idea that more prominent firms are more likely to be covered.[16] To address the selection issue, in Section 5.6, I will show that the results remain consistent when correcting for selection bias using inverse probability weighting (Wooldridge, 2002,

[16]We also find systematic patterns of news mentions over the startup life cycle and around the time of financing in Figure A.5. While Panel (a) and Panel (b) show the probability of news mentions and financing news mentions by age, respectively, Panel (c) and Panel (d) present the probability of news mentions and financing news mentions around a two-year window of financing events. On average, startups have the lowest probability of news mentions in the first quarter of their founding, and the probability of news mentions increases until the startup reaches its third year of operation. After that, the probability of news mentions remains stable over time. Meanwhile, the probability of financing news mentions remains stable except at the time of financing is extremely high, and then drops sharply. These patterns suggest that the selection of news mentions is also related to the startup age and the time around the financing event.

2007).

Market Sentiment Does the measure of financing risk also capture other unobservable factors? One potential concern is that the measure could be simply another version of sentiment about venture capital and entrepreneurial activities, which captures the overall tone of the news articles and outlook conveyed in news articles about the industry. To shed light on this concern, I construct two leading dictionary-based sentiment measures on the same set of news articles, the sentiment measures from Loughran and McDonald (2011, LM) and Garcia, Hu and Rohrer (2023, GHR). While the two sets of measures are derived from the same text data, they are conceptually different. Indeed, I show in Section 5.6 that the financing risk measure has a much more robust correlation with entrepreneurial activities, while the two sentiment measures have a less clear relationship with entrepreneurial activities.

Startup Quality In constructing our financing risk measure, I explicitly exclude the information related to the startups' internal operations and performance. However, I can utilize these pieces of information on startup quality to develop a separate measure that reflects risk stemming specifically from startup quality. Specifically, I construct a measure of quality risk using a procedure similar to that of the financing risk measure but focused solely on information related to the startup's operational conditions and performance. Figure A.4 shows the prompt format used to query GPT to construct the measure of quality risk. In this query, I ask GPT to concentrate exclusively on information related to the startup's operational condition and performance that could influence future financing availability, while excluding other factors, such as capital supply conditions. In Section 5.6, this quality risk measure will be used as a control variable to further support the argument that our results are not driven by the omitted startup quality.

3.3. The Properties of Financing Risk

3.3.1. Illustrative Examples

Before turning to the properties of the measure of financing risk, I provide two illustrative examples to provide some intuitions on the measure. For these examples, I provide the responses from GPT and related information on the news article.

The first example is a news article from the Wall Street Journal, published on December 3, 1991, titled "Year One: New Entrepreneurs Confront the Task: After Fairly Quick Start, New Businesses Hit First Turn."[17] This article discusses the challenges faced by three new ventures, including Biosyn Inc., a Philadelphia-based manufacturer of AIDS-prevention products. Despite an initially optimistic outlook, Biosyn still faced significant challenges and eventually sought business alliances overseas. The co-founder, Anne-Marie Corner, rated the long-term survival chances of Biosyn higher than ever, due to securing high-value projects overseas. However, the main concern for Biosyn remained future funding. As stated in the article, "Operating the company while scrambling to raise $2 million in the next 18 months, she says, 'is like running toward the edge of a cliff and hoping there's a trampoline at the bottom.' " The financing risk from GPT is 1, with the reason being "The article highlights Biosyn's struggles in securing funding, indicating constraints on financing for new ventures, particularly in a recession." This example clearly illustrates the concept of financing risk. Even with a promising product and market, a startup's financing risk can be high if securing future funding is difficult.

The methodology of measuring financing risk can distinguish between existing funding availability and future funding availability. As an example, consider a news article from the Wall Street Journal, published on November 16, 2016, titled "Supersonic Jet Takes Shape — A demonstrator from Boom Technology, a startup, is expected to take to air next year."[18] This article discusses the progress of Boom Technology, a startup that is developing a supersonic jetliner. While Boom Technology "has initial support from several venture funds", the article highlights the challenges and uncertainties associated with the project,

[17] The link to the news article from ProQuest is https://www.proquest.com/docview/398321760/abstract/772DBF118E124F66PQ.

[18] The link to the news article from ProQuest is https://www.proquest.com/docview/1839489150/35D0A093E8A8485APQ.

particularly the need for future funding to complete the development and certification of the aircraft. The financing risk from GPT is 1, with the reason being "The article mentions uncertainty in future funding for Boom Technology, indicating potential constraints on financing."

3.3.2. Financing Risk Over Time and Across Industries

To assess the validity and richness of the financing risk measure, I examine both its time-series properties and its cross-sectional variation across industries. Figure 2 plots the quarterly average of the financing risk index (red line) against aggregate venture capital activity (blue line). The aggregate financing risk index lines up well with the major trends in the venture capital market, with a correlation of -0.58. The aggregate index remained at high values during the first several years of the 1990s and then experienced sharp decreases from the early 1990s to 2000. Indeed, this was a period of rapid growth in the venture capital market, as the internet bubble took off. The Nasdaq crash in 2000 and the global financial crisis in 2008 virtually shook the entire venture capital industry, which coincides with the two peaks in aggregate financing risk. From 2010 onward, the measure trended downward, consistent with the fact that venture capital continued to show phenomenal growth since then.

[Insert Figure 2 Here.]

To further benchmark the measure, Figure A.6 compares our measure to other related measures. In Panel (a), I include survey-based measures of credit conditions from the Small Business Economic Trends (SBET) survey by the National Federation of Independent Business[19], with a correlation coefficient of -0.39, indicating that the financing risk measure provides valuable insights into future financing conditions. Panels (b) and (c) plot our measure against the LM and GHT sentiment measures, with correlations of -0.82

[19]The NFIB SBET survey data can be accessed at http://www.nfib-sbet.org/. The NFIB SBET survey, conducted monthly from 1986 to 2024, gathers small business owners' expectations regarding the economy, access to credit, and investment plans. It is widely recognized as a proxy for small business sentiment. The key question from the survey that I use is: "Do you expect to find it easier or harder to obtain your required financing during the next three months?" I plot the quarterly average percentage of respondents who believe credit conditions will be "easier" minus those who believe conditions will be "harder".

and -0.56, respectively. These relationships suggest that our index is informative about the overall sentiment toward venture capital activities.

I also explore cross-sectional variation in financing risk across industries in Figure A.7, revealing substantial cross-industry heterogeneity that reflects underlying differences in business models, investor expectations, and capital intensity. Startups in consumer products and services (B2C), business services (B2B), and financial services exhibit higher levels of financing risk, likely due to their sensitivity to demand cycles and revenue-based growth business models. In contrast, information technology and healthcare startups consistently face lower financing risk, reflecting their established role in venture portfolios and well-understood innovation pathways. Energy and materials sectors span the distribution, capturing their internal diversity from capital-intensive traditional industries to newer, more investable clean technologies. These patterns indicate that our measure captures not only cyclical macro-financial conditions but also persistent, industry-specific characteristics that shape how startups perceive the likelihood of future funding constraints.

3.3.3. Financing Risk and Startup Life Cycle

I further examine how financing risk evolves over the startup life cycle. Panel (a) of Figure 3 shows average financing risk by age during the first ten years since founding, controlling for startup fixed effects and time fixed effects. Interestingly, contrary to conventional assumptions, the financing risk is lowest in the earliest years and gradually increases as startups age. This pattern reflects the structured nature of venture capital financing. Early-stage startups typically operate on recently raised funding and benefit from investor optimism during the post-funding runway. At this stage, expectations are calibrated around long-term vision and milestones yet to be reached. However, as startups grow older and begin approaching their next critical financing round, investors expect startups' progress toward product milestone, customer traction, and profitability. Startups that fail to meet these rising expectations will face a greater perceived risk of future funding constraints. This rising trend in financing risk over time illustrates the forward-looking nature of our measure, capturing not just startup fundamentals but also dynamic expectations about funding sustainability at each stage of development.

[Insert Figure 3 Here.]

I next explore how a startup's financing risk responds directly to receiving new venture capital investment. Specifically, I conduct an event study of financing risk in a four-year window surrounding a venture capital financing event, again controlling for startup and time fixed effects. Panel (b) of Figure 3 shows the estimates of financing risk relative to the quarter prior to the financing event. Financing risk remains relatively flat in the quarters leading up to funding and is statistically indistinguishable from zero. At the time of the funding event, however, financing risk drops sharply by approximately 0.03, suggesting a temporary easing of capital concerns. This decline is short-lived: financing risk returns to pre-event levels within two quarters and continues to rise thereafter, consistent with the interpretation that startups quickly resume planning for future rounds and that investor expectations continue to escalate. These results provide further support for the view that financing risk is forward-looking and sensitive to the evolving funding cycle of ventures.

To further understand how financing risk varies across startups with different growth trajectories, I examine its cross-sectional relationship with key startup characteristics. Figure A.8 plots average financing risk against the log of cumulative VC financing in Panel (a) and the log of employment in Panel (b), controlling for state-industry-time fixed effects. Both panels exhibit a clear U-shaped pattern. Startups with low levels of capital or small size of employment face the highest perceived financing risk, consistent with their limited track records, shorter runways, and greater uncertainty about future viability. As startups raise more capital or expand their workforce, financing risk declines, reflecting increased investor confidence and milestone achievements. However, beyond a certain point, financing risk begins to rise again. This upward trend reflects both the increasing capital demands of larger startups and the higher expectations from investors. On one hand, later-stage startups require more resources to sustain growth, making them more dependent on continued access to funding. On the other hand, investors expect these startups to demonstrate measurable progress toward scale, revenue, or exit. When the startups' demands and investors' expectations mismatch, perceived financing risk increases. This U-shape pattern reinforces the forward-looking nature of our measure, showing that financing risk reflects not just startup size or funding history, but whether the startup's current trajectory aligns with investor expectations at each stage of growth.

3.3.4. Financing Risk and Future Financing Activities

I empirically validate the financing risk measure by examining its relationship with subsequent startup financing outcomes. If the measure captures forward-looking concerns about capital availability, it should be predictive of actual financing behavior. Table 1 presents the results with the full sample of startup-quarter panel in Columns (1)-(4). Columns (1)-(2) report estimates for the probability of receiving VC financing over the next four quarters, while Columns (3)-(4) examine the log amount of VC financing received. I control for state-industry-time fixed effects in Columns (1) and (3), and add startup fixed effects in Columns (2) and (4) to account for time-invariant startup characteristics. I also control a set of startup characteristics that are commonly associated with VC financing. Columns (5)-(8) repeat the analysis using a subsample of startups that received external financing within the past six quarters. This subsample helps rule out the possibility that the results are driven by financial constraints or endogenous selection into financing activity.

[Insert Table 1 Here.]

Across all specifications, I find strong and consistent evidence that financing risk is predictive of future financing outcomes. Startups with higher financing risk are significantly less likely to raise venture capital in the following year, and when they do, raise less funding. These patterns confirm that the financing risk measure captures meaningful forward-looking variation in startups' external funding prospects and aligns closely with investor behavior. The results underscore that our measure is not simply reactive to past startup outcomes, but anticipates future financing constraints as perceived by the market.

3.4. Descriptive Statistics

Table 2 shows the summary statistics for the financing risk and other related measures and startup characteristics in the startup-quarter panel. Panel (a) reports statistics for the full sample, which includes U.S. VC-backed startups with available financing risk measures from their founding year through either exit or their twentieth year of operation, covering the period from 2000 to 2023. Panels (b) through (d) focus on the subsample of startups that received external financing within the past six quarters. This subsample serves as the primary focus of the empirical analysis, helping to mitigate concerns about confounding effects from contemporaneous financial constraints or selection into financing activity, as discussed in Section 2.

[Insert Table 2 Here.]

Panel (a) presents summary statistics for the financing risk and related sentiment variables. The average value of financing risk is 0.12, with a standard deviation of 0.19. The median is 0.05, and the 90th percentile is 0.27, suggesting that, on average, news coverage conveys relatively positive expectations about startups' future access to funding. Similar distributions are observed in the quality risk measure, the LM sentiment index, and the GHR sentiment index, with most startups exhibiting relatively favorable outlooks in the text data. As shown in Panel (b), the subsample of recently financed startups exhibits broadly similar patterns, supporting its use as a comparison group in the baseline analysis.

Panel (c) and Panel (d) present the summary statistics for the startup characteristics in the current period and over the next four quarters, respectively. On average, startups raise VC financing in 38% of quarters, with an average financing size of 12 million dollars. The median startup in our sample is 20 quarters (five years) old and has 38 employees. The typical startup holds 0.17 trademarks and 0.48 patents. Exit events remain rare at the startup-quarter level: the average probability of an IPO is 1.0%, a merger and acquisition is 1.7%, and a bankruptcy is 0.2%. However, when measured at the startup level, the probability is more substantial, where 6.7% of startups eventually go public, 31% are acquired, and 4.5% experience bankruptcy.

4. Empirical Strategy

4.1. Baseline Specification

The empirical strategy is directly guided by the model developed in Section 2, which highlights the importance of forward-looking financing risk in shaping entrepreneurial decisions and outcomes. The baseline specification aims to test the Hypotheses 1-4, by estimating the relationship between a startup's financing risk and its subsequent performance using a startup-quarter panel between 2000 and 2023:

$$Y_{f,t+4} = \beta_1 FinRisk_{f,t} + \gamma_1 X_{f,t} + \xi_f + \xi_{S(f)\times I(f)\times t} + \varepsilon_{1,f,t+4}, \tag{15}$$

where $Y_{f,t+4}$ is the outcome of interest for startup f over the next 4 quarters from quarter $t+1$ to quarter $t+4$. To test Hypothesis 1, I examine the outcomes as the log number of patents and the log number of citation-weighted patents, as well as the log number of patents varying by their risky and resource-intensive status. For Hypothesis 2, I use the log number of employment as a common proxy for startup growth, and the log number of product trademarks as a proxy for startup milestones. To test Hypothesis 3, I examine the outcomes as an indicator of whether a startup goes to IPO, whether it is acquired, or whether it files for bankruptcy.

The variable of interest, $FinRisk_{f,t}$, measures the startup-specific perception of financing risk at time t, constructed from a news-based textual analysis. Higher values of $FinRisk_{f,t}$ indicate a stronger concern about future capital availability, consistent with the model's theoretical construction of forward-looking financing risk. The coefficient β_1 can be interpreted as the semi-elasticity of the outcome of interest with respect to the financing risk, which captures the changes in the outcome of interest when the financing risk increases from 0 to 1.

I control for a comprehensive set of time-varying covariates, $X_{f,t}$ in the model to account for factors that may influence the relationship between financing risk and startup outcomes, including the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log VC funding in the current and prior four quarters, cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. These controls help mitigate concerns that observed correlations between financing risk and outcomes may be driven by startup size, funding cycles, or media visibility.

4.2. Instrumental Variables Strategy

While baseline specification in Equation (15) includes rich covariates and fixed effects, concerns remain a concern. Changes in financing risk may be correlated with unobserved factors, such as shifts in startup quality and investment opportunities, which may also affect startup performance. To address this, I adopt an instrumental variables (IV) strategy that isolates exogenous variation in financing risk driven by aggregate uncertainty shocks.

The identification strategy is motivated directly by the model's definition of financing risk in Section 2, where beliefs about future funding depend not only on startup fundamentals but also on prevailing macroeconomic conditions. The key idea is that when macroeconomic uncertainty increases, startups may anticipate a more volatile fundraising environment, even if their fundamentals remain unchanged. This belief, in turn, raises perceived financing risk and influences their strategic decisions (Dibiasi, Mikosch and Sarferaz, 2025).

A key identification challenge lies in separating the second-moment effects of uncertainty from the first-moment effects because increases in uncertainty often coincide with directional movements in underlying economic variables. For example, sharp drops in oil prices are frequently accompanied by spikes in oil price volatility. Failing to account for changes in the level of economic fundamentals may conflate the effects of uncertainty.

Following Bloom (2009) and Jurado, Ludvigson and Ng (2015), I construct our instrument using exogenous variation in aggregate uncertainty at the time the financing risk is measured.[20] Specifically, I use the first principal component of the nine aggregate price uncertainty shocks from Alfaro, Bloom and Lin (2024), including the two-month standard deviation of daily growth rates on crude oil prices, the two-month standard deviation of daily growth rates in seven major bilateral exchange rates against the US dollar (foreign currency units per US$1),[21] and the two-month average of EPU from Baker, Bloom and Davis (2016). To control for correlated first-moment movements, I include the first prin-

[20] If multiple news articles are available within the same quarter, I use the earliest publication date.

[21] They include the euro, Canadian dollar, Japanese yen, British pound, Swiss franc, Australian dollar, and Swedish krona. Each of these trades widely in currency markets outside their respective home areas and (along with the US dollar) are referred to by Board staff as major currencies. See http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf for more details.

cipal component of the two-month returns in oil and exchange rates and the quarterly growth in government expenditure as a share of GDP. [22] I divide the uncertainty shocks and their first-moment returns by 100 for readability. The decision to use a two-month window is somewhat arbitrary. Later I will show that the results are robust to using a one-month window or a three-month window.

The implementation of the instrumental variable follows closely Bernstein (2015). First, I assign each startup the values of the macro uncertainty shocks based on the earliest date of the news article in quarter t used to construct its financing risk. This timing ensures that our instruments are predetermined with respect to the outcomes measured in subsequent quarters and reflect the macroeconomic environment at the time the financing risk is formed. Then, I estimate the first-stage regression of the financing risk on the aggregate uncertainty shocks:

$$FinRisk_{f,t} = \beta_2 Uncertainty_{f,t} + \pi_2 Return_{f,t} + \gamma_2 X_{f,t} + \xi_f + \xi_{S(f)\times I(f)\times t} + \varepsilon_{2,f,t+4}, \tag{16}$$

where $Uncertainty_{f,t}$ is the instrumental variable as the first principal component of the nine aggregate price uncertainty shocks, and $Return_{f,t}$ is the first principal component of the corresponding first-moment returns. The second-stage equation estimates the impact of financing risk on the startup's outcome:

$$Y_{f,t+4} = \beta_3 \widehat{FinRisk}_{f,t} + \pi_3 Return_{f,t} + \gamma_3 X_{f,t} + \xi_f + \xi_{S(f)\times I(f)\times t} + \varepsilon_{3,f,t+4}, \tag{17}$$

where $\widehat{FinRisk}_{f,t}$ is the predicted financing risk from Equation (16). If the conditions for a valid instrumental variable are met, which we will discuss in the next section, β_3 captures the causal effect of financing risk on the startup's outcome. We implement the instrumental variable estimator using two-stage least squares (2SLS). Standard errors are clustered at the startup level throughout.

[22] For oil and currencies, the first moments are the two-month growth rates of daily oil spot prices and exchange rates. For economic policy uncertainty, I use the growth of quarterly government expenditures as a share of gross domestic product. I obtain the daily price of oil and currencies and the government expenditure share from the St. Louis Fed, and the EPU measure from Baker, Bloom and Davis (2016). Figure A.9 shows the time series of the aggregate uncertainty shocks and their first-moment returns, aggregated at the quarter level.

By explicitly controlling for the first-moment returns of the energy, currencies, and policy uncertainty shocks, I isolate the uncertainty (i.e., second-moment) effect from correlated first-moment effects. Startup fixed effects (ξ_f) absorb time-invariant unobserved heterogeneity. State-by-industry-by-period fixed effects ($\xi_{S(f)\times I(f)\times t}$), defined over five-year intervals, control for potential differences in regional and industry exposure to uncertainty shocks. For example, startups in California, New York, and Massachusetts account for over 50% of the sample, and industries differ markedly in their exposure to energy or currency volatility.

Finally, consistent with the model, the main analysis focuses on a subsample of startup-quarter observations that are less likely to be financially constrained. Specifically, I restrict to startups that received external external financing within the past six quarters.[23] These recently funded startups are less likely to be financially constrained, typically representing high-quality ventures with promising investment opportunities, which allows us to further isolate the impact of financing risk on entrepreneurial activities, independent of current financial constraints. Later I will use the subsample of non recently funded startups to test the effects of financing risk when current liquidity is a binding constraint, which further illustrates the distinct effects of financing risk and financial constraints.

4.3. Financing Risk and Uncertainty Shocks

Relevance Condition For the instrumental variables strategy to be valid, the aggregate uncertainty shocks must significantly influence financing risk. I plot the time series of average financing risk alongside the aggregate uncertainty shocks and their corresponding first-moment returns in Figure 4. From this figure, I can see that financing risk is strongly correlated with aggregate uncertainty shocks, with a correlation coefficient of 0.56, but only weakly correlated with first-moment returns (correlation of 0.08). This pattern is consistent with the model's implication that startups interpret higher macro uncertainty as a signal of a more volatile and less favorable funding environment, thus raising their perceived financing risk.

[23]Typical time between startup funding rounds is two to three years. See https://carta.com/data/venture-fundraising-early-stage-startups-2022.

[Insert Figure 4 Here.]

Table 3 presents the first-stage regression results. In Column (1), I estimate Equation (16) without additional covariates and find a statistically significant coefficient of 0.558 on the aggregate uncertainty shocks. In Column (2), I include the full set of controls from the baseline specification in Equation (15), and the coefficient remains stable and significant. A one standard deviation increase in aggregate uncertainty leads to a 0.6 percentage point increase in financing risk, that is, 0.6% higher probability of limited future funding. The first-stage F-statistic of 123.8 in Column (2) confirms that the instrument is strong and unlikely to suffer from weak instrument bias. While our main uncertainty shocks use the first principal component of the nine aggregate price uncertainty shocks, I also replicate the analysis by including the second principal component in Column (3). While the coefficient on the first principal component is similar in magnitude and statistical significance, the coefficient on the second principal component is statistically significant at the 5% level, suggesting that our measure of uncertainty shocks captures most of the variation in aggregate uncertainty shocks.

[Insert Table 3 Here.]

To explore possible nonlinear effects, Columns (4) use a dummy variable equal to one if the startup experiences a "large" uncertainty shock—defined as a shock in the top 20% in the sample period. I find that these large shocks are associated with a 1.9 percentage point increase in perceived financing risk. In Columns (5) and (6), I replicate the analysis using one-month and three-month windows to test robustness. I find that the results are stable, and the F-statistics remain high (ranging from 103 to 127), indicating the instrument's strength is not sensitive to the choice of time window used to construct the shocks.

One potential concern is that the effect of macroeconomic uncertainty on financing risk may not be strictly contemporaneous. If uncertainty shocks are highly persistent, or if news articles are written in response to earlier macro conditions, or if perceived financing risk evolves with a lag, then past uncertainty shocks could still predict financing risk, raising questions about whether our instrument captures truly exogenous variation. To address this concern, Columns (7)-(9) include both the contemporaneous uncertainty shock and its lagged value measured two months, one quarter, and two quarters before the date of financing risk, respectively. In all cases, I find that only the contemporaneous shock significantly predicts financing risk, while the lagged shocks are statistically insignificant. This pattern is particularly informative given the persistence of the uncertainty shocks over time, where the correlation with shocks two months prior is 0.69, one quarter prior is 0.56, and two quarters prior is 0.34. It reinforces the interpretation that startups form beliefs about future funding availability in response to the current macroeconomic environment, rather than to past uncertainty and that our instrument captures the timing and source of this belief formation with precision.

Together, these results provide strong evidence that uncertainty shocks have a strong effect on startup-level financing risk. The effects are stronger during periods of large aggregate shocks, and they appear orthogonal to observed startup characteristics and their first-moment fluctuations.

It is worth noting that the instrumental variables estimates identify a local average treatment effect, which applies to the subset of startups whose perceived financing risk responds to variation in the instrument (Angrist and Imbens, 1995). In this context, the "compliers" are startups whose beliefs about future funding availability shift when macroeconomic uncertainty changes. This assumption is well-aligned with our setting, as early-stage startups who often rely on external financing and are operate without stable cash flow are likely to be sensitive to signals about broader market volatility.

Exclusion Restriction The instrument of aggregate uncertainty shocks needs to not only affect financing risk but also satisfy the exclusion restriction. That is, aggregate uncertainty shocks must affect startup outcomes only through the perceived financing risk.

To support this assumption, our empirical design incorporates several layers of controls and validation tests. First, our empirical design includes state-by-industry-by-period fixed effects, which absorb differences in how regions and industries respond to macroeconomic conditions. For example, certain industries (such as energy or biotech) or states (such as California or Texas) may be more sensitive to oil prices or policy uncertainty. By accounting for these interactions over five-year periods, I rule out the possibility that the instrument captures time-varying, region- or industry-specific effects.

Second, I explicitly control for the first-moment component of the macroeconomics variable used in constructing the instrument. By holding these directional movements constant, I isolate the second-moment effect on financing risk. I also include rich startup-level time-varying controls such as VC funding history, age, employment, and media coverage to account for startup-specific dynamics that could confound the results.

Third, I implement a placebo test using lagged uncertainty shocks that are measured before the formation of financing risk. If the exclusion restriction is violated, the alternative channels of the uncertainty shocks should also be apparent when exploring the uncertainty shocks that occurred before the date when the financing risk was formed. Table A.5 presents the placebo results using the log number of patents as the outcome. Column (1) shows the reduced-form results using the contemporaneous uncertainty shocks, where the coefficient is negative and statistically significant. Column (2) uses uncertainty shocks measured two months before the financing risk, where the coefficient is small and statistically insignificant. Columns (3)-(4) repeat this test using uncertainty shocks lagged by one and two quarters, respectively, and again find no significant effect. In Columns (5)-(7), I include both contemporaneous and lagged shocks in the same regression. The coefficient on the contemporaneous shock remains stable and significant, while the lagged shocks remain insignificant. This finding is especially compelling given the high persistence of uncertainty shocks. If alternative channels were driving the relationship between uncertainty and startup outcomes, such as persistent changes in credit markets, lagged shocks should also have predictive power. The absence of such effects suggests that the relevant channel operates exclusively through contemporaneous beliefs about financing conditions, supporting the validity of the exclusion restriction.

Taken together, these findings support the validity of our IV strategy. The instrument is both relevant and plausibly excludable, allowing us to interpret our estimates as the causal effect of financing risk on entrepreneurial outcomes as driven by changes in macroeconomic uncertainty.

5. Financing Risk, Startup Innovation, and Growth

The model developed in Section 2 highlights a central feature of startup dynamics: financing risk, the forward-looking uncertainty about a startup's ability to raise external capital in future rounds, can shape strategic behavior in the absence of current financial constraints. As shown in the model, this belief-based risk emerges naturally in settings with staged financing, where continuation depends not only on realized performance but also on expectations about investor willingness to provide follow-on funding. While this structure allows investors to stage commitments and mitigate downside risk (Gompers, 1995; Cornelli and Yosha, 2003; Bergemann and Hege, 2005; Bergemann, Hege and Peng, 2009), it places entrepreneurs in a position of strategic uncertainty. Anticipating the possibility of future funding shortfalls, startups may alter their investment strategy, growth plans, or exit timing. These effects are particularly salient for high-potential ventures that are actively managing toward ambitious milestones and rely heavily on external financing to reach scale (Nanda and Rhodes-Kropf, 2017).

The model motivates four empirical hypotheses. The first three subsections provide evidence for Hypothesis 1-3, where I focus on a subsample of recently funded startups that are less likely to face immediate capital shortages but still exposed to forward-looking financing uncertainty, and examine how variation in financing risk shapes outcomes in innovation, growth, and survival. In Section 5.4, I further examine the effects of financing risk when their current liquidity is a binding constraint, which provides evidence for Hypothesis 4.

5.1. Financing Risk and Startup Innovation Strategy

Young and high-growth startups, particularly those backed by venture capital, contribute disproportionately to novel and radical innovations (Kortum and Lerner, 2000; Samila and Sorenson, 2011; Akcigit and Kerr, 2018). Given the important role of these startups in innovation and economic growth, it is important to understand how forward-looking funding concerns shape their innovative activity, especially those novel and breakthrough innovations. However, according to Hypothesis 1, startups facing greater financing risk are predicted to adopt more conservative innovation strategies and avoid projects that are especially risky or capital-intensive. In this section, I examine whether financing risk affects the quantity and novelty of innovation output in Section 5.1.1 and the direction of innovation in Section 5.1.2.

5.1.1. Innovation Quantity and Novelty

The first set of results explores the effect of financing risk on innovation quantity and novelty in Table 4. I focus on two measures of innovation: the log number of patents in Columns (1)-(3) and the log number of citation-weighted patents in Columns (4)-(6). All specifications follow the model described in Section 4.1.

The results consistently show a strong and negative relationship between financing risk and future innovation outcomes. In Column (1) of Table 4, I report the endogenous OLS model and find a small but statistically significant negative association between financing risk and future patenting activity. Column (2) presents the reduced-form estimation in which the endogenous financing risk measure is replaced with the aggregate uncertainty shocks used as instruments. The coefficient on uncertainty shocks is statistically significant and negative, indicating that uncertainty shocks have a negative effect on future innovation outcomes arguably through the impact on financing risk. In Column (3), I report the 2SLS estimates, where financing risk is instrumented using aggregate uncertainty shocks. The coefficient on the financing risk is significant and equals -0.798, indicating that a 0.1 probability increase in financing risk leads to an 8.0% reduction in the number of patents filed over the next year.

[Insert Table 4 Here.]

Beyond the number of patents, the quality and novelty of innovation are equally important, where I use citation-weighted patents as a proxy in Columns (4)-(6). The 2SLS estimate in Column in Column (6) yields a coefficient of -0.980, suggesting the patents filed by startups with 0.1 probability of higher financing risk receive approximately 9.8% fewer citations compared to the patents filed in the same classification and period. Both effects are statistically significant and economically sizable, especially when considering that the average number of patents is 2.1 and the average number of citation-weighted patents is 6.9.

Interestingly, the OLS estimates are smaller in magnitude than the IV estimates. This suggests that the selection bias associated with higher financing risk is positive, and startups that face high financing risk yet still manage to innovate may be positively selected on unobservables, such as underlying technological potential or founder quality. In other words, more ambitious or capital-intensive ventures, which require greater external funding, may also face greater financing risk precisely because their projects are harder to fund, even though they may be highly innovative if successful. This is consistent with the empirical relationship between financing risk and startup past VC financing and employment size in Section 3.3.3, where I find that beyond a certain level, startups with more past VC financing and employment size are more likely to face higher financing risk.

These results provide strong support for Hypothesis 1, showing that perceived financing risk significantly reduces both the quantity and quality of startup innovation. Importantly, these effects are observed among startups that recently secured VC funding, reinforcing the model's prediction that forward-looking financing concerns shape strategic direction even in the absence of immediate financial constraints.

5.1.2. Innovation Direction and Riskiness

To further directly test Hypothesis 1, I examine whether financing risk affects the type of innovation startups pursue. Specifically, I investigate whether startups facing higher perceived financing risk shift away from riskier, more exploratory forms of innovation. To do so, I leverage the richness of patent data by focusing on different innovation characteristics, including product versus process innovation (Bena and Simintzi, 2024), high versus low originality innovation (Trajtenberg, Henderson and Jaffe, 1997), explorative vs. exploitative innovation (Almeida, Hsu and Li, 2013) and (Custódio, Ferreira and Matos, 2019), and high versus low breakthrough innovation (Kelly et al., 2021). Table 5 provides estimates by categorizing a startup's patent portfolio based on these innovation characteristics, where all specifications use 2SLS estimation.

[Insert Table 5 Here.]

Across all dimensions, I find consistent evidence that startups facing higher financing risk significantly reduce their engagement in more resource-intensive and riskier innovation. Columns (1) and (2) separate the patent portfolio into product and process innovation categories. 0.1 probability increase in financing risk is associated with a statistically significant 5.4% decrease in the log number of product patents, while the effect on process patents in Column (2) is smaller in magnitude (3.3%) and only marginally significant. This is consistent with the notion that under concerns about future financial constraints, startups may prioritize process improvements that focus on labor productivity improvements and are often complementary to existing investments while delaying riskier and more resource-intensive product development (Berndt, 1990; Kogan, Papanikolaou and Stoffman, 2020).

In Columns (3)-(4), I find that financing risk has a strong negative effect on high originality patents with a coefficient of -0.614 but has no significant impact on low originality ones, suggesting that startups under financial uncertainty tend to avoid novel technological combinations. This pattern is echoed in Columns (5)-(6), where startups facing higher financing risk file fewer high explorative patents with a coefficient of -0.698, and the effect on low explorative innovation is near zero and statistically insignificant. This pattern reinforces the idea that startups facing financing risk are less able to pursue exploratory innovations that rely on untested knowledge, and may instead focus on safer, more incremental projects that rely on existing knowledge.

Regarding breakthrough innovations, financing risk has a particularly pronounced effect on high-breakthrough-score patents, with a coefficient of -0.817 in Column (7), compared to an insignificant and even positive coefficient of 0.158 for low-breakthrough-score patents in Column (8). This finding indicates that financing risk disproportionately affects breakthrough innovations. This is aligned with the notion that high-impact innovations often require substantial financial resources (Kerr and Nanda, 2015; Nanda and Rhodes-Kropf, 2013), and startups with higher financing risk are more likely to delay or abandon such efforts.

Taken together, these results indicate that financing risk not only reduces the overall quantity of innovation but also shifts the direction of innovation away from projects that are more uncertain, exploratory, or transformative. These findings align closely with the model's prediction that startups facing financing risk will strategically avoid risky and capital-intensive innovation in favor of safer, more incremental projects. Hence, all these results reinforce the forward-looking, strategic nature of financing risk as a constraint on entrepreneurial behavior.

5.2. Financing Risk, Startup Growth, and Milestones

Next, to test Hypothesis 2, I examine whether financing risk affects startups' ability to grow and reach operational milestones. Specifically, I assess how perceived financing risk influences two key indicators of scaling progress, including employment growth and product development activities. Table 6 presents the results, using the log number of employees in Columns (1)-(3) and the log number of product trademarks in Columns (4)-(6) as the dependent variables. Here, Trademarks serve as a proxy for milestone achievement, particularly for startups progressing toward commercialization. The results from 2SLS estimation demonstrate a strong and negative relationship between financing risk and both employment growth and product development activities.

[Insert Table 6 Here.]

In Column (1), the OLS estimate shows a statistically significant coefficient of -0.086, indicating that a 0.1 probability increase in financing risk is associated with a 0.86% reduction in employment over the following year. The effect becomes even larger and more precisely estimated in the 2SLS specification in Column (3), where the coefficient is -1.986. This implies that a 0.1 increase in the probability of facing future financing constraints reduces employment by nearly 20%. This effect is economically sizeable, especially when considering the average number of employees is 326 in our sample. This suggests that startups facing higher financing risk are less likely to hire additional employees, reflecting a more cautious approach to growth when future funding is uncertain.

The coefficient of financing risk on product development, as measured by trademark registrations, follows a similar pattern. The 2SLS estimate in Column (6) yields a significant coefficient of -0.924, implying that a 0.1 probability increase in financing risk reduces trademark activity by 9.2%. This suggests that while startups facing higher financing risk may continue to operate, they are more conservative with their branding and product development efforts.

Consistent with the Hypothesis 2, startups facing higher financing risk are consistently more conservative in employment growth and product development over the long term. Even among recently funded startups, which are less likely to face immediate liquidity concerns, concerns about future capital availability appear to dampen hiring and slow product development.

5.3. Financing Risk and Startup Survival

To test Hypothesis 3, I examine whether financing risk influences startup exit outcomes, specifically, the likelihood of exit via IPO, merger or acquisition (M&A), or bankruptcy. Table 7 reports the results using indicators for each exit type measured over the subsequent four quarters.

[Insert Table 7 Here.]

Columns (1)-(3) focus on IPO outcomes. While the OLS estimate in Column (1) is statistically insignificant, the 2SLS estimate in Column (3) yields a coefficient of -0.225, significant at the 1% level. This suggests that a 0.1 probability increase in financing risk leads to a 2.3 percentage point reduction in the likelihood of successful IPO exit over the next four quarters. This is an economically meaningful drop, given the baseline probability of successful IPO exit is only 1.7% at the startup-quarter level and 6.7% at the startup level. This result is consistent with the idea that high financing risk forces startups to delay or forgo IPO plans, especially among late-stage startups in our sample, which have an average age of 6 years and a median size of 283 employees.

Columns (4)-(6) examine the likelihood of M&A exits, and the results show that financing risk has a negative effect. The 2SLS estimate in Column (6) is -0.120 and marginally significant, suggesting that a 0.1 increase in financing risk reduces the probability of an acquisition by approximately 1.2 percentage points. Although modest, this effect is notable given that the average M&A probability is only 1.9% at the startup-quarter level and 31%

at the startup level. This is consistent with the idea that startups facing heightened financing risk may fail to make significant innovation and product development, thus becoming less attractive targets.

In contrast, Columns (7)-(9) show that financing risk significantly increases the likelihood of failure. While the OLS estimate in Column (7) is 0.007, the 2SLS estimate in Column (9) is 0.055 and statistically significant at the 5% level. This implies that a 0.1 increase in financing risk raises the probability of failure by nearly 5.5 percentage points, nearly three times the base failure rate of 0.2% per quarter. These findings underscore the causal link between perceived financing risk and survival. If they anticipate future capital shortages, even recently funded startups are more likely to exit through failure rather than strategic or successful channels.

Taken together, these results strongly support Hypothesis 3. Financing risk meaningfully reduces the likelihood of positive exits (IPO and M&A) and raises the probability of failure. These patterns reinforce the idea that forward-looking expectations about capital access are critical determinants of startup trajectories and survival, even in the absence of immediate capital shortfalls.

5.4. Financing Risk and Current Financial Constraints

I further test our last prediction in Hypothesis 4 by examining the effects of financing risk on startup behavior when current liquidity is a binding constraint. This is motivated by the idea that when a startup is currently facing financial constraints, its strategy is primarily determined by its financial capacity rather than forward-looking beliefs about future capital. Specifically, I repeat our 2SLS specifications using a sample of startups that have not received external financing in the past six quarters. These startups, which are the complement to our baseline "post-financing" sample, are more likely to include startups facing binding financial constraints, such as limited cash reserves or inability to access capital markets. This setting allows us to test whether financing risk still predicts startup behavior when startups are more directly subject to contemporaneous liquidity constraints.

[Insert Table 8 Here.]

Table 8 presents the results for this constrained sample. Across most outcomes, including innovation quantity and quality, trademarks, and exit through IPO and M&A, I find that the estimated coefficients on financing risk are statistically insignificant. The one exception is employment: financing risk continues to exhibit a negative and statistically significant effect on hiring decisions even in the absence of recent funding. This pattern suggests that when startups are budget-constrained, they are less able to adjust their strategies in response to forward-looking beliefs about capital availability. Instead, their decisions are likely to be driven primarily by immediate financial capacity.

There are two notable exceptions. First, employment remains negatively and significantly associated with financing risk, though the magnitude of the effect is smaller (-5.3%) than in the baseline sample. This suggests that hiring decisions remain responsive to both current and anticipated funding conditions, even when startups are constrained right now. Second, bankruptcy has a marginally positive association with financing risk, indicating that perceived financing risk may amplify the likelihood of failure, as the startups are operating near their financial margin and any additional concerns about funding availability could push them over the edge. In both cases, the findings reflect a channel through which financing risk may still affect outcomes on the margin, although other strategic decisions are largely frozen by capital constraints.

These results are consistent with the model's prediction in Hypothesis 4. When startups are financially constrained, their optimal strategy is primarily shaped by what they can afford, not what they expect. In such cases, current financial constraints dominate, and financing risk becomes a less relevant determinant of strategic behavior. The muted effects of financing risk on most outcomes in this subsample contrast sharply with the baseline results, where unconstrained startups exhibit strong forward-looking responses to financing risk.

5.5. Heterogeneous Effects by Startup Characteristics

To further understand how financing risk affects entrepreneurial outcomes, we examine heterogeneous effects by VC stage, startup size, and startup age. These cross-sectional comparisons help test whether startups at different phases of development or with different organizational capacities respond differently to anticipated capital constraints.

I begin by splitting the sample based on the VC stage in Table A.6. Panel (a) reports estimates for early-stage startups, defined as those that have not yet received late-stage VC funding, and Panel (b) focuses on late-stage startups that have received at least one round of late-stage VC. Across nearly all outcomes, I find larger effects of financing risk among late-stage startups. This includes stronger negative coefficients for innovation quantity and quality, trademarks, and exit through IPO and M&A. One possible explanation is that late-stage startups face more immediate expectations of performance, making them more exposed to changes in perceived financing risk. These startups are also likely to be operating at larger scale, and thus need to make more capital-intensive decisions, amplifying the impact of capital uncertainty. Interestingly, one exception is employment, where early-stage startups appear more sensitive. This may reflect the fact that hiring decisions at earlier stages are more flexible, or that late-stage startups maintain minimum staffing levels despite uncertainty.

I next examine heterogeneity by startup size, using the median number of employees each quarter as the cutoff. Panel (a) of Table A.7 reports results for small-size startups and Panel (b) for large-size startups. The findings mirror those by the VC stage, where the effects of financing risk are generally larger and more significant among large startups, especially for innovation, trademarks, and exit outcomes. Larger startups tend to have more defined product strategies, structured teams, and investor expectations. As a result, their strategic decisions are more sensitive to funding prospects. Again, employment is the exception, where financing risk has a slightly stronger effect on employment among smaller startups.

I also conduct a parallel heterogeneity analysis by startup age in Table A.8, splitting the sample into those less than or equal to five years old and those older than five years. The results are generally indistinguishable across age groups, with only employment showing a statistically significant effect for young startups.

Taken together, these heterogeneity results suggest that the real effects of financing risk are stronger for startups that are closer to exit, operating at scale, or under more intense investor scrutiny. However, early-stage and small startups are more sensitive in terms of employment, possibly due to their limited resources and greater operational flexibility. These patterns highlight the layered nature of financing risk, that is, its consequences depend not only on startup-level exposure but also on how exposed a startup is to funding expectations, growth commitments, and capital needs.

5.6. Robustness

Robustness of Post-Financing Sample Period Our baseline analysis focuses on startups that received external financing within the past six quarters. This restriction is motivated by the model's emphasis on unconstrained startups that are not currently limited by liquidity but are still exposed to forward-looking financing risk. To test the sensitivity of our results to this sample definition, I explore two narrower post-financing windows in Table A.10.[24] In Panel (a), I restrict the sample to startups that received VC funding within the past two quarters, and in Panel (b), within the past four quarters. Across both tighter definitions, I find estimates that are consistent with the baseline with similar in sign and slightly larger in magnitude, especially for post-financing periods of two quarters. This pattern is in line with the model's logic, where the nearer a startup is to its most recent funding event, the more likely it is to be unconstrained, and the more prominently forward-looking financing risk influences its behavior.

Sample Selection Correction One of the potential concerns discussed in Section 3.2.3 is that our measure of financing risk depends on startups being mentioned in news articles, and the probability of being mentioned is not randomly distributed across startups, which may introduce sample selection bias in our empirical analysis. To directly address this concern, I apply inverse probability weighting to correct for selection bias, following (Wooldridge, 2002, 2007). Specifically, I first use a Probit model to estimate the probability of being mentioned in news articles as a function of the covariates in Equation (15), along with four additional controls: the number of VC news mentions and financing news mentions in the past four quarters, and the cumulative number of VC and financing news

[24] I explore repeat the 2SLS specifications using the full sample of startups, without conditioning on recent funding history in Table A.9. While the magnitude of coefficients is attenuated, the estimated effects of financing risk remain directionally consistent. This is consistent with the model's prediction on Lemma 1 that unconstrained startups are more likely to be sensitive to financing risk.

mentions. These additional variables account for the likelihood of being mentioned in news articles. Next, I predict the probability of being mentioned based on the estimated model and reweight the sample accordingly using the predicted probabilities. In Table A.11, we reweight the sample based on the probability of financing news mentions. The results indicate that the effects of financing risk remain consistent when correcting for selection bias in our sample through inverse probability weighting.

Is The Measure of Financing Risk Another Proxy for Market Sentiment? One potential concern about our measure is that our measure may capture factors beyond the forecast of future funding availability, such as general market sentiment about venture capital and entrepreneurial activities. To address this, I construct two representative dictionary-based sentiment measures on the same text of news articles, using the sentiment measures from Loughran and McDonald (2011, LM) and Garcia, Hu and Rohrer (2023, GHR). In Table A.12, I further include controls for LM sentiment and GHR sentiment measures to verify that the observed effects of financing risk are not simply driven by general market sentiment. The results show that the financing risk measure remains significant, whereas the sentiment measures themselves exhibit much weaker effects. This finding supports the distinctiveness of financing risk from general market sentiment, confirming it as a stronger and more consistent predictor of startup activity.

Are The Effects of Financing Risk Driven by Startup Quality? Our analysis so far, using our novel measure of financing risk, highlights its significant impact on startups' growth, innovation, and survival. However, an alternative explanation could be that our results are driven by the omitted startup quality that is not explicitly controlled for in our baseline specification. To address this concern, I construct an alternative measure of quality risk, as outlined in Section 3.2.3. While our financing risk measure focuses solely on information related to future funding availability, the quality risk measure is designed to capture only information specific to a startup's quality, internal operations, and performance. In Table A.13, I add the quality risk measure as an additional covariate to our baseline specification across various outcomes. I observe that the effects of financing risk remain statistically and economically significant, suggesting that financing risk has a distinct and independent impact on startup outcomes that is not solely attributable to startup quality.

6. Conclusion Remarks

This paper provides new insights into the role of financing risk, the forward-looking belief that a startup may face limited access to external capital in the future, as a critical determinant of entrepreneurial behavior. I develop a simple dynamic model of intertemporal investment in the context of staged financing. I show that financing risk, distinct from traditional financial constraints, distorts investment, growth, and survival decisions. To test the model, I construct a novel text-based measure of financing risk using natural language processing applied to over four million startup-specific news articles that are linked to U.S. venture-backed startups. The measure captures real-time market perceptions and has a clear interpretation of the predicted probability of future funding limitations.

Our empirical analysis focuses on recently funded startups, the ones that are unlikely to be currently financially constrained but still exposed to forward-looking uncertainty. Using an instrumental variable strategy that exploits the exogenous variation from macroeconomic uncertainty shocks, I find that financing risk reduces both the quantity and quality of innovation, with especially pronounced effects on exploratory, novel, and capital-intensive innovations. Financing risk also significantly slows employment growth, delays product development, and increases the probability of failure. These effects are concentrated among startups that are not liquidity-constrained, while the effects are attenuated among financially constrained startups. This pattern is consistent with the model's prediction that financing risk only shapes behavior when firms have the flexibility to respond to expectations.

Financing risk introduces a distinct and influential channel through which future funding uncertainty alters the strategic choices, growth trajectory, and survival of a startup. The results underscore the importance of managing a startup's expectations about future funding availability, not just securing current capital. In this context, it becomes critical for entrepreneurs and investors to consider strategies for mitigating financing risk. One potential approach is to reduce the frequency of capital raising rounds by taking larger chunks of money at each stage, though doing so may limit the value of staged commitments and abandonment options (Kerr, Nanda and Rhodes-Kropf, 2014; Nanda and Rhodes-Kropf, 2017). Future research could explore a range of potential strategies to mitigate the effects of financing risk, as well as whether targeted policy interventions, such as funding guarantees or counter-cyclical VC programs, could help reduce the shadow of financing risk in uncertain markets.

References

Acharya, Viral V, Douglas Gale, and Tanju Yorulmazer. 2011. "Rollover risk and market freezes." *Journal of Finance*, 66(4): 1177–1209.

Agrawal, Ajay, Joshua S Gans, and Scott Stern. 2021. "Enabling entrepreneurial choice." *Management Science*, 67(9): 5510–5524.

Akcigit, Ufuk, and William R Kerr. 2018. "Growth through heterogeneous innovations." *Journal of Political Economy*, 126(4): 1374–1443.

Alfaro, Iván, Nicholas Bloom, and Xiaoji Lin. 2024. "The finance uncertainty multiplier." *Journal of Political Economy*, 132(2): 577–615.

Almeida, Heitor, Murillo Campello, and Michael S Weisbach. 2011. "Corporate financial and investment policies when future financing is not frictionless." *Journal of Corporate Finance*, 17(3): 675–693.

Almeida, Heitor, Po-Hsuan Hsu, and Dongmei Li. 2013. "Less is more: Financial constraints and innovative efficiency." *Available at SSRN 1831786*.

Angrist, Joshua D, and Guido W Imbens. 1995. "Two-stage least squares estimation of average causal effects in models with variable treatment intensity." *Journal of the American statistical Association*, 90(430): 431–442.

Arellano, Cristina, Yan Bai, and Patrick J Kehoe. 2019. "Financial frictions and fluctuations in volatility." *Journal of Political Economy*, 127(5): 2049–2103.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson. 2024. "Artificial intelligence, firm growth, and product innovation." *Journal of Financial Economics*, 151: 103745.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. "Measuring economic policy uncertainty." *Quarterly Journal of Economics*, 131(4): 1593–1636.

Barberis, Nicholas. 2018. "Psychology-based models of asset prices and trading volume." In *Handbook of Behavioral Economics: Applications and Foundations 1*. Vol. 1, 79–175. Elsevier.

Bena, Jan, and Elena Simintzi. 2024. "Machines could not compete with Chinese labor: Evidence from US firms' innovation." *Available at SSRN 2613248*.

Bergemann, Dirk, and Ulrich Hege. 2005. "The financing of innovation: Learning and stopping." *RAND Journal of Economics*, 719–752.

Bergemann, Dirk, Ulrich Hege, and Liang Peng. 2009. "Venture capital and sequential investments."

Bernanke, Ben S. 1983. "Irreversibility, uncertainty, and cyclical investment." *Quarterly Journal of Economics*, 98(1): 85–106.

Berndt, Ernst R. 1990. "Energy use, technical progress and productivity growth: A survey of economic issues." *Journal of Productivity Analysis*, 2: 67–83.

Bernstein, Shai. 2015. "Does going public affect innovation?" *Journal of Finance*, 70(4): 1365–1403.

Bernstein, Shai, Xavier Giroud, and Richard R Townsend. 2016. "The impact of venture capital monitoring." *Journal of Finance*, 71(4): 1591–1622.

Bienz, Carsten, and Julia Hirsch. 2012. "The dynamics of venture capital contracts." *Review of Finance*, 16(1): 157–195.

Bloom, Nicholas. 2009. "The impact of uncertainty shocks." *Econometrica*, 77(3): 623–685.

Bolton, Patrick, Shannon Liu, Ramana Nanda, and Savitar Sundaresan. 2024. "Moral hazard in experiment design: Implications for financing innovation."

Boyle, Glenn W, and Graeme A Guthrie. 2003. "Investment, uncertainty, and liquidity." *Journal of Finance*, 58(5): 2143–2166.

Brunnermeier, Markus K, and Martin Oehmke. 2013. "The maturity rat race." *Journal of Finance*, 68(2): 483–521.

Bybee, J Leland. 2023. "The ghost in the machine: Generating beliefs with large language models." *arXiv preprint arXiv:2305.02823*.

Bybee, Leland, Bryan Kelly, Asaf Manela, and Dacheng Xiu. 2021. "Business news and business cycles." *Journal of Finance*.

Camuffo, Arnaldo, Alessandro Cordova, Alfonso Gambardella, and Chiara Spina. 2020. "A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial." *Management Science*, 66(2): 564–586.

Camuffo, Arnaldo, Alfonso Gambardella, Fabio Maccheroni, Massimo Marinacci, and Andrea Pignataro. 2022. "Microfoundations of low-frequency high-impact decisions."

Cornelli, Francesca, and Oved Yosha. 2003. "Stage financing and the role of convertible securities." *Review of Economic Studies*, 70(1): 1–32.

Custódio, Cláudia, Miguel A Ferreira, and Pedro Matos. 2019. "Do general managerial skills spur innovation?" *Management Science*, 65(2): 459–476.

Davis, Jesse, Adair Morse, and Xinxin Wang. 2020. "The leveraging of silicon valley." *National Bureau of Economic Research Working Paper*.

Devlin, Jacob. 2018. "Bert: Pre-training of deep bidirectional transformers for language understanding." *arXiv preprint arXiv:1810.04805*.

Dibiasi, Andreas, Heiner Mikosch, and Samad Sarferaz. 2025. "Uncertainty shocks, adjustment costs and firm beliefs: Evidence from a representative survey." *American Economic Journal: Macroeconomics*, 17(3): 36–73.

Dixit, Avinash. 1989. "Entry and exit decisions under uncertainty." *Journal of Political Economy*, 97(3): 620–638.

Froot, Kenneth A, and Jeremy C Stein. 1998. "Risk management, capital budgeting, and capital structure policy for financial institutions: An integrated approach." *Journal of Financial Economics*, 47(1): 55–82.

Froot, Kenneth A, David S Scharfstein, and Jeremy C Stein. 1993. "Risk management: Coordinating corporate investment and financing policies." *Journal of Finance*, 48(5): 1629–1658.

Gans, Joshua S, David H Hsu, and Scott Stern. 2002. "When does start-up innovation spur the gale of creative destruction?" *RAND Journal of Economics*, 571–586.

Gans, Joshua S, Scott Stern, and Jane Wu. 2019. "Foundations of entrepreneurial strategy." *Strategic Management Journal*, 40(5): 736–756.

Garcia, Diego, Xiaowen Hu, and Maximilian Rohrer. 2023. "The colour of finance words." *Journal of Financial Economics*, 147(3): 525–549.

Gilchrist, Simon, Jae W Sim, and Egon Zakrajšek. 2014. "Uncertainty, financial frictions, and investment dynamics." *National Bureau of Economic Research Working Paper*.

Goetzmann, William N, Dasol Kim, and Robert J Shiller. 2022. "Crash narratives." *National Bureau of Economic Research Working Paper*.

Gompers, Paul A. 1995. "Optimal investment, monitoring, and the staging of venture capital." *Journal of Finance*, 1461–1489.

Gompers, Paul Alan, and Joshua Lerner. 2004. *The venture capital cycle.* MIT press.

Gompers, Paul, and Josh Lerner. 2001. "The venture capital revolution." *Journal of Economic Perspectives*, 15(2): 145–168.

Gompers, Paul, Anna Kovner, Josh Lerner, and David Scharfstein. 2008. "Venture capital investment cycles: The impact of public markets." *Journal of Financial Economics*, 87(1): 1–23.

Hall, Robert E, and Susan E Woodward. 2010. "The burden of the nondiversifiable risk of entrepreneurship." *American Economic Review*, 100(3): 1163–1194.

Hellmann, Thomas, and Manju Puri. 2002. "Venture capital and the professionalization of start-up firms: Empirical evidence." *Journal of Finance*, 57(1): 169–197.

Hennessy, Christopher A, Amnon Levy, and Toni M Whited. 2007. "Testing Q theory with financing frictions." *Journal of Financial Economics*, 83(3): 691–717.

He, Zhiguo, and Wei Xiong. 2012*a*. “Dynamic debt runs.” *Review of Financial Studies*, 25(6): 1799–1843.

He, Zhiguo, and Wei Xiong. 2012*b*. “Rollover risk and credit risk.” *Journal of Finance*, 67(2): 391–430.

Howell, Sabrina T, Josh Lerner, Ramana Nanda, and Richard R Townsend. 2020. “How resilient is venture-backed innovation? Evidence from four decades of US patenting.” *National Bureau of Economic Research Working Paper*.

Hsu, David H. 2006. “Venture capitalists and cooperative start-up commercialization strategy.” *Management Science*, 52(2): 204–219.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng. 2015. “Measuring uncertainty.” *American Economic Review*, 105(3): 1177–1216.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy. 2021. “Measuring technological innovation over the long run.” *American Economic Review: Insights*, 3(3): 303–320.

Kerr, William R, and Ramana Nanda. 2011. “Financing constraints and entrepreneurship.” *Handbook of Research on Innovation and Entrepreneurship. Cheltenham: Elgar*, 88–103.

Kerr, William R, and Ramana Nanda. 2015. “Financing innovation.” *Annual Review of Financial Economics*, 7(1): 445–462.

Kerr, William R, Josh Lerner, and Antoinette Schoar. 2014. “The consequences of entrepreneurial finance: Evidence from angel financings.” *Review of Financial Studies*, 27(1): 20–55.

Kerr, William R, Ramana Nanda, and Matthew Rhodes-Kropf. 2014. “Entrepreneurship as experimentation.” *Journal of Economic Perspectives*, 28(3): 25–48.

Kim, Chang-Soo, David C Mauer, and Ann E Sherman. 1998. “The determinants of corporate liquidity: Theory and evidence.” *Journal of Financial and Quantitative Analysis*, 33(3): 335.

Kogan, Leonid, Dimitris Papanikolaou, and Noah Stoffman. 2020. “Left behind: Creative destruction, inequality, and the stock market.” *Journal of Political Economy*, 128(3): 855–906.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence DW Schmidt, and Bryan Seegmiller. 2021. “Technology, vintage-specific human capital, and labor displacement: Evidence from linking patents with occupations.” *National Bureau of Economic Research Working Paper*.

Kortum, Samuel, and Josh Lerner. 2000. “Assessing the contribution of venture capital to innovation.” *RAND Journal of Economics*, 31(4): 674–692.

Krishnan, Karthik, Debarshi K Nandy, and Manju Puri. 2015. "Does financing spur small business productivity? Evidence from a natural experiment." *Review of Financial Studies*, 28(6): 1768–1809.

Lerner, Josh, Junxi Liu, Jacob Moscona, and David Y Yang. 2024. "Appropriate entrepreneurship? The rise of China and the developing world." *National Bureau of Economic Research Working Paper*.

Lerner, Josh, Morten Sorensen, and Per Strömberg. 2011. "Private equity and long-run investment: The case of innovation." *Journal of Finance*, 66(2): 445–477.

Loughran, Tim, and Bill McDonald. 2011. "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks." *Journal of Finance*, 66(1): 35–65.

Manso, Gustavo. 2011. "Motivating innovation." *Journal of Finance*, 66(5): 1823–1860.

McDonald, Robert, and Daniel Siegel. 1986. "The value of waiting to invest." *Quarterly Journal of Economics*, 101(4): 707–727.

Nanda, Ramana, and Matthew Rhodes-Kropf. 2013. "Investment cycles and startup innovation." *Journal of Financial Economics*, 110(2): 403–418.

Nanda, Ramana, and Matthew Rhodes-Kropf. 2017. "Financing risk and innovation." *Management Science*, 63(4): 901–918.

Ozmel, Umit, David T Robinson, and Toby E Stuart. 2013. "Strategic alliances, venture capital, and exit decisions in early stage high-tech firms." *Journal of Financial Economics*, 107(3): 655–670.

Pindyck, Robert S. 1988. "Capital risk and models of investment behaviour." In *Economic modelling in the OECD countries*. 103–117. Springer.

Puri, Manju, and Rebecca Zarutskie. 2012. "On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms." *Journal of Finance*, 67(6): 2247–2293.

Samila, Sampsa, and Olav Sorenson. 2011. "Venture capital, entrepreneurship, and economic growth." *Review of Economics and Statistics*, 93(1): 338–349.

Smith, Clifford W, and Rene M Stulz. 1985. "The determinants of firms' hedging policies." *Journal of Financial and Quantitative Analysis*, 20(4): 391–405.

Spence, Michael. 1973. "Job market signaling." *Quarterly Journal of Economics*, 87(3): 355–374.

Thakor, A V. 1990. "Investment "myopia" and the internal organization of capital allocation decisions." *Journal of Law, Economics, and Organization*, 6(1): 129–154.

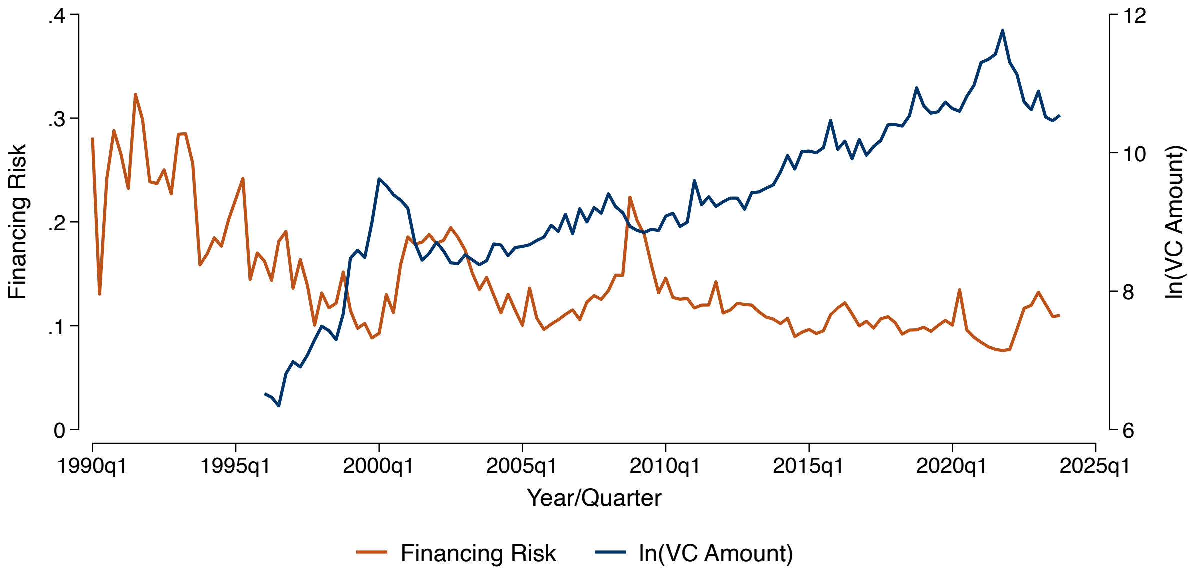
Trajtenberg, Manuel, Rebecca Henderson, and Adam Jaffe. 1997. "University versus corporate patents: A window on the basicness of invention." *Economics of Innovation and new technology*, 5(1): 19–50.

Turc, Iulia, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. "Well-read students learn better: On the importance of pre-training compact models." *arXiv preprint arXiv:1908.08962*.

Wooldridge, Jeffrey M. 2002. "Inverse probability weighted M-estimators for sample selection, attrition, and stratification." *Portuguese Economic Journal*, 1(2): 117–139.

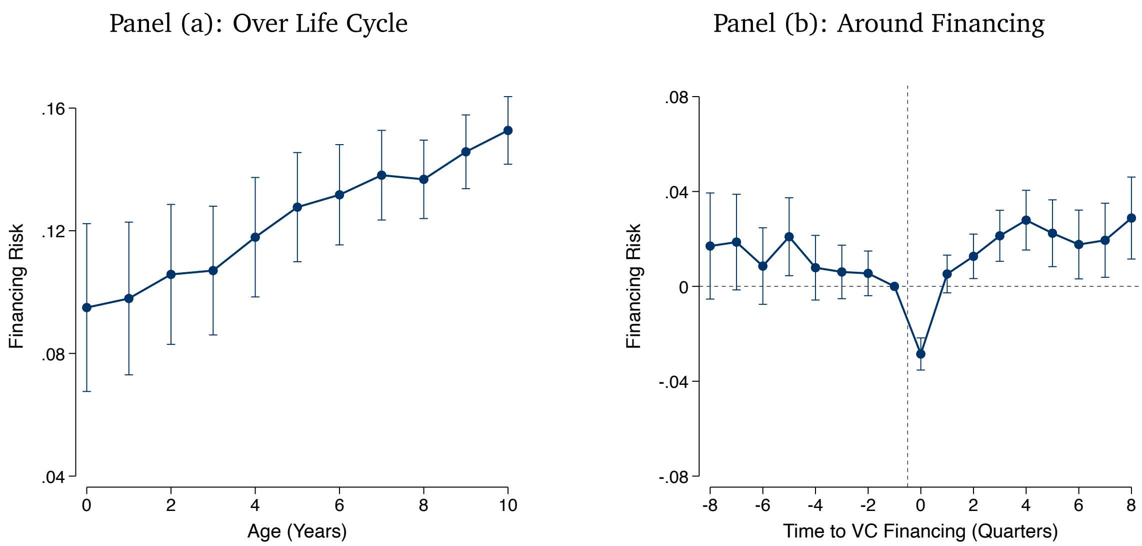
Wooldridge, Jeffrey M. 2007. "Inverse probability weighted estimation for general missing data problems." *Journal of Econometrics*, 141(2): 1281–1301.

Figure 2. Financing Risk and VC Activity Over Time



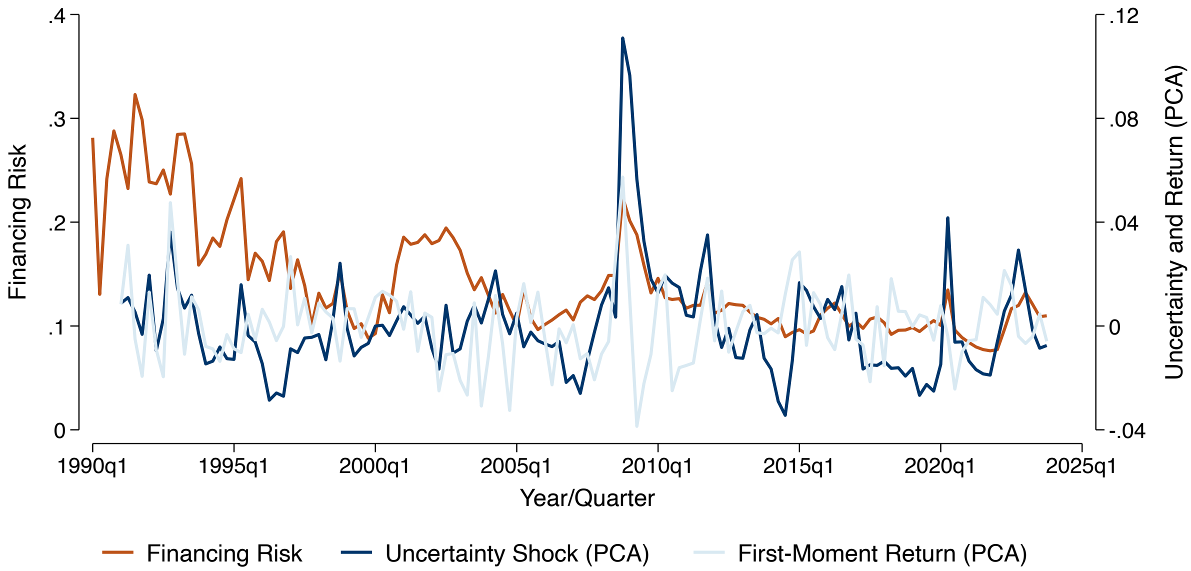
Notes. This figure presents the time series of average financing risk and VC activity. The red line is the quarterly average financing risk using the startup-quarter panel that we constructed in Section 3.2.2, and the blue line is the log amount of VC deals.

Figure 3. Financing Risk Over Life Cycle and Around Financing



Notes. This figure presents the average financing risk over startup's life cycle in Panel (a) and around startup financing events in Panel (b). In Panel (b), we conduct an event study of the financing risk over a four-year window surrounding the venture capital financing event. The estimates are normalized to the financing risk in the quarter preceding the financing event. In both panels, we include startup fixed effects and time fixed effects. All the estimations are weighted by Kaplan-Meier hazard rate over age and the probability of being mentioned in VC financing news. The sample includes all U.S. VC-backed startups with available financing risk measures. Standard errors are clustered at the startup level.

Figure 4. Financing Risk and Uncertainty Shocks



Notes. This figure presents the sensitivity of average financing risk to uncertainty shocks. The red line is the quarterly average financing risk using the startup-quarter panel that we constructed in Section 3.2.2. The dark blue line is the uncertainty shocks, constructed as the first principal component of the nine aggregate price shocks from Alfaro, Bloom and Lin (2024), including the two-month standard deviation of daily growth rates on crude oil prices, the two-month standard deviation of daily growth rates in seven major bilateral exchange rates against the US dollar (foreign currency units per US$1; the euro, Canadian dollar, Japanese yen, British pound, Swiss franc, Australian dollar, and Swedish krona), and the two-month average of EPU from Baker, Bloom and Davis (2016). The light blue line is the first-moment of the uncertainty shocks, constructed as the first principal component of the first-moment returns of the nine shocks. For oil and currencies, the first-moments are the two-month growth rates of daily oil spot prices and exchange rates. For economic policy uncertainty, we use the growth of quarterly government expenditures as a share of gross domestic product. We divide the uncertainty shocks and its first-moment returns by 100 for readability.

Table 1. Measure Validation: Financing Risk and Financing Activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Y_{f,t+4}$ =	1(VC Deal)		ln(VC Deal Amount)		1(VC Deal)		ln(VC Deal Amount)	
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Sample	Full	Full	Full	Full	Post	Post	Post	Post
Financing Risk$_{f,t}$	-0.074***	-0.029***	-0.183***	-0.145***	-0.054***	-0.037***	-0.147***	-0.206***
	(0.009)	(0.008)	(0.026)	(0.027)	(0.013)	(0.013)	(0.043)	(0.047)
$Y_{f,t}$	-0.022***	-0.113***	-0.001	-0.094***	-0.034***	-0.147***	-0.012**	-0.089***
	(0.004)	(0.005)	(0.005)	(0.009)	(0.005)	(0.006)	(0.005)	(0.010)
$Y_{f,t-1,t-4}$	0.139***	-0.006	0.196***	0.033***	0.123***	-0.052***	0.182***	0.023**
	(0.004)	(0.005)	(0.007)	(0.010)	(0.005)	(0.006)	(0.007)	(0.012)
Observations	101,791	89,566	101,791	89,566	65,811	55,184	65,811	55,184
R-squared	0.110	0.437	0.136	0.433	0.109	0.449	0.137	0.441
No. of Firms	28,474	16,249	28,474	16,249	22,977	12,350	22,977	12,350
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Startup Control Variables	No	Yes	No	Yes	No	Yes	No	Yes

Notes. This table validate the financing risk measure by examining the relation between financing risk and startup financing activities over the next four quarters. The outcome variables include an indicator of whether a startup receives VC financing over the next four quarters (1(VC Deal)) in Columns (1)-(2) and Columns (5)-(6) and the amount of VC financings over the next four quarters (ln(VC Deal Amount)) in Columns (3)-(4) and Columns (7)-(8). Financing Risk$_{f,t}$ is constructed following the procedure in Section 3.2.2. Controls include the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. All variables are defined and described in Table 2. The model includes state-industry fixed effects and time fixed effects in Columns (1), (3), (5), and (7) and startup fixed effects and time fixed effects in Columns (2), (4), (6), and (8). The sample used in Columns (1)-(2) and (5)-(6) includes all U.S. VC-backed startups with available financing risk measures, and the sample used in Columns (3)-(4) and (7)-(8) is a subsample of startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Descriptive Statistics at the Firm-Quarter Panel

	count	mean	sd	min	p10	p50	p90	max
Panel (a): Financing Risk and Other Related Measures: Full Sample								
Financing Risk$_{f,t}$	114,084	0.115	0.186	0.031	0.036	0.048	0.268	0.956
Quality Risk$_{f,t}$	114,084	0.166	0.270	0.01	0.011	0.014	0.5	0.992
Sentiment (LM)$_{f,t}$	114,084	0.573	1.176	-17.82	-0.68	0.48	2.027	9.764
Sentiment (GHR)$_{f,t}$	114,084	0.599	0.701	-4.667	-0.148	0.529	1.453	13.462
VC News$_{f,t}$	114,084	15.682	126.423	1	1	3	17	8,765
Financing News$_{f,t}$	114,084	3.776	20.690	1	1	2	5	1,493
Panel (b): Financing Risk and Other Related Measures: Post-Financing Sample								
Financing Risk$_{f,t}$	73,821	0.102	0.168	0.031	0.035	0.046	0.197	0.956
Quality Risk$_{f,t}$	73,821	0.136	0.250	0.01	0.011	0.013	0.5	0.992
Sentiment (LM)$_{f,t}$	73,821	0.640	1.184	-10.291	-0.638	0.559	2.117	8.937
Sentiment (GHR)$_{f,t}$	73,821	0.611	0.698	-4.281	-0.147	0.543	1.477	10
VC News$_{f,t}$	73,821	12.385	110.292	1	1	3	13	8,765
Financing News$_{f,t}$	73,821	3.558	16.811	1	1	2	5	1,284
Panel (c): Startup Characteristics in the Current Period: Post-Financing Sample								
1(VC Deal)$_{f,t}$	73,821	0.380	0.485	0	0	0	1	1
VC Deal Amount$_{f,t}$	73,821	11.919	92.130	0	0	0	25	12,800
VC Deal Amount (Past 4Q)$_{f,t-4,t-1}$	73,821	23.463	181.265	0	0	0	40	14,035
VC Deal Amount (Cumulative)$_{f,-\infty,t}$	73,821	95.741	506.507	0	0.375	18.616	168.699	24,281
Age$_{f,t}$	73,821	24.311	17.469	0	6	20	50	80
Patent$_{f,t}$	73,821	0.478	3.721	0	0	0	1	293
Citation-Weighted Patent$_{f,t}$	73,821	1.659	16.919	0	0	0	1.166	1471.731
Employment$_{f,t}$	73,821	282.803	2026.508	0	4	38	403	96985
Trademark$_{f,t}$	73,821	0.167	0.766	0	0	0	0	41
IPO$_{f,t}$	73,821	0.010	0.100	0	0	0	0	1
Merger & Acquisition$_{f,t}$	73,821	0.017	0.128	0	0	0	0	1
Bankruptcy$_{f,t}$	73,821	0.002	0.047	0	0	0	0	1
Panel (d): Startup Characteristics Over the Next 4 Quarters: Post-Financing Sample								
Patent$_{f,t+4}$	66,593	2.092	15.205	0	0	0	3	721
Citation-Weighted Patent$_{f,t+4}$	66,593	6.916	58.907	0	0	0	8.605	3542.041
Employment$_{f,t+4}$	66,382	326.368	2190.472	0	5	47	481	93421
Trademark Count$_{f,t+4}$	66,593	0.624	1.972	0	0	0	2	85
IPO$_{f,t+4}$	66,593	0.017	0.130	0	0	0	0	1
Merger & Acquisition$_{f,t+4}$	66,593	0.019	0.138	0	0	0	0	1
Bankruptcy$_{f,t+4}$	66,593	0.003	0.054	0	0	0	0	1

Notes. This table summarizes startup-quarter level characteristics, including financing risk and other related measures for the full sample in Panel (a) and for the post-financing sample in Panel (b), startup characteristics in the current period for the post-financing sample in Panel (c), and startup characteristics over the next 4 quarters for the post-financing sample in Panel (d). Financing Risk$_{f,t}$ is constructed following the procedure in Section 3.2.2. Quality Risk$_{f,t}$ captures the uncertainty of the startup's quality that could influence future funding availability, as defined in Section 3.2.3. Sentiment (LM)$_{f,t}$ and Sentiment (GHR)$_{f,t}$ are two measures of sentiments from Loughran and McDonald (2011) and Garcia, Hu and Rohrer (2023), respectively. VC News$_{f,t}$ is the number of news articles related to entrepreneurship and venture capital, and Financing News$_{f,t}$ is the number of news articles related to financing. We report the following variables in the current period in Panel (c) and over the next 4 quarters in Panel (d): 1(VC Deal)$_{f,t}$ is an indicator of whether a startup receives VC financing; VC Deal Amount$_{f,t}$ is the amount of VC financings; VC Deal Amount (Past 4Q)$_{f,t-4,t-1}$ is the amount of VC financings over the past four quarters; VC Deal Amount (Cumulative)$_{f,t}$ is the cumulative amount of VC financing; Age$_{f,t}$ is the startup's age in quarters; Patent$_{f,t}$ is number of patents; Citation-Weighted Patent$_{f,t}$ is the citation-weighted patents; Employment$_{f,t}$ is startup's employment; Trademark$_{f,t}$ is the number of product trademarks; IPO$_{f,t}$ is an indicator of whether a startup goes public; Merger & Acquisition$_{f,t}$ is an indicator of whether a startup is acquired; Bankruptcy$_{f,t}$ is an indicator of whether a startup goes bankrupt or out of business.

Table 3. First Stage: Financing Risk and Uncertainty Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Y_{f,t}$ =	Financing Risk$_{f,t}$								
Instrument	Baseline			Robustness Test			Placebo Test		
	2-Month			Binary	3-Month	1-Month	2-Month		
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Uncertainty Shocks$_{f,t}$	0.558***	0.608***	0.562***	1.892***	0.613***	0.555***	0.583***	0.600***	0.618***
	(0.054)	(0.055)	(0.057)	(0.248)	(0.054)	(0.055)	(0.067)	(0.061)	(0.056)
First Moment$_{f,t}$	-0.080	-0.082	-0.091*	0.646***	-0.070	-0.034	-0.068	-0.075	-0.082
	(0.051)	(0.050)	(0.052)	(0.230)	(0.050)	(0.049)	(0.052)	(0.052)	(0.051)
Uncertainty Shocks (2nd PC)$_{f,t}$			0.147**						
			(0.070)						
First Moment (2nd PC)$_{f,t}$			-0.229**						
			(0.093)						
Uncertainty Shocks (2M Before)$_{f,t-1}$							0.079		
							(0.065)		
First Moment (2M Before)$_{f,t-1}$							-0.085*		
							(0.048)		
Uncertainty Shocks (1Q Before)$_{f,t-1}$								0.037	
								(0.059)	
First Moment (2Q Before)$_{f,t-1}$								-0.050	
								(0.048)	
Uncertainty Shocks (2Q Before)$_{f,t-1}$									0.004
									(0.050)
First Moment (2Q Before)$_{f,t-1}$									-0.081*
									(0.047)
Effective F-statistic	107	123.8	55.93	58.15	127	103.2	65.91	62.90	63.20
Observations	53,804	53,804	53,804	53,804	53,804	53,804	53,804	53,804	53,804
R-squared	0.347	0.357	0.357	0.355	0.357	0.356	0.357	0.357	0.357
No. of Firms	11,981	11,981	11,981	11,981	11,981	11,981	11,981	11,981	11,981
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the first-stage estimation of the instrumental variables analysis, following the regression specification in Equation (16). The dependent variable, Financing Risk$_{f,t}$, is the financing risk of a startup f in quarter t, which is instrumented by the first principal component of the nine aggregate price uncertainty shocks, including the two-month standard deviation of daily growth rates on crude oil prices, the two-month standard deviation of daily growth rates in seven major bilateral exchange rates against the US dollar, and the two-month average of EPU from Baker, Bloom and Davis (2016). The first moment of the aggregate price uncertainty shocks is the first principal component of the corresponding first-moment returns, as defined in Section 4.1. We divide the uncertainty shocks and its first-moment returns by 100 for readability. In Columns (1)-(3), we use the baseline instrument with two-month window, and we add the second principal component in Columns (3). Column (4) replaces the baseline instrument with a dummy variable equal to one if the startup experiences a "large" uncertainty shock, defined as a shock in the top 20% in the sample period. We also replace the first-moment returns with a dummy variable equal to one if it is in the bottom 20% in the sample period. Column (5)-(6) perform the robustness tests by using an instrument with one-month window and an instrument with three-month window, respectively. Column (7)-(9) perform the placebo tests including both the contemporaneous uncertainty shock and its lagged values measured two months, one quarter, and two quarters prior to the date of financing risk, respectively. In Columns (2)-(9), controls include the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log VC funding in the current and prior four quarters, cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. All variables are defined and described in Table 2. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Financing Risk and Startup Innovation Quantity and Novelty

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{f,t+4}$ =	ln(Patent)			ln(Citation-Weighted Patent)		
Model	OLS	OLS	2SLS	OLS	OLS	2SLS
Financing Risk$_{f,t}$	-0.040***		-0.798***	-0.053***		-0.980***
	(0.013)		(0.239)	(0.020)		(0.361)
Uncertainty Shocks$_{f,t}$		-0.485***			-0.596***	
		(0.140)			(0.213)	
$Y_{f,t}$	0.194***	0.194***	0.192***	0.118***	0.118***	0.116***
	(0.016)	(0.016)	(0.017)	(0.013)	(0.013)	(0.013)
$Y_{f,t-1,t-4}$	0.138***	0.137***	0.139***	0.075***	0.074***	0.074***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
First-Stage F-Statistic			124			123.7
Observations	53,804	53,804	53,804	53,804	53,804	53,804
No. of Firms	11,981	11,981	11,981	11,981	11,981	11,981
R-squared	0.838	0.838	0.003	0.816	0.816	-0.020
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup innovation over the next four quarters. The outcome variables include the log number of patents (ln(Patent)) in Columns (1)-(3) and the log number of citation-weighted patents (ln(Citation-Weighted Patent)) in Columns (4)-(6). Financing Risk$_{f,t}$ is constructed following the procedure in Section 3.2.2. Uncertainty Shocks$_{f,t}$ is the first principal component of the nine aggregate price uncertainty shocks, and First Moment$_{f,t}$ is the first principal component of the corresponding first-moment returns, as defined in Section 4.1. We divide the uncertainty shocks and its first-moment returns by 100 for readability. Controls include the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log VC funding in the current and prior four quarters, cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. All variables are defined and described in Table 2. The model includes startup fixed effects and state-industry-period fixed effects in all columns. In Columns (1)-(2) and (4)-(5), the model is estimated using OLS. In Columns (3) and (6) it is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Financing Risk and Startup Innovation Direction and Riskiness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Y_{f,t+4}$ =	ln(Patent w/ Specific Characteristics)							
	Product/Process		Originality		Explorative		KPST Breakthrough	
	Product	Process	High	Low	High	Low	High	Low
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.543**	-0.332**	-0.614***	-0.141	-0.698***	-0.054	-0.817**	0.158
	(0.216)	(0.167)	(0.220)	(0.126)	(0.189)	(0.202)	(0.355)	(0.400)
$Y_{f,t}$	0.063**	0.131***	-0.002	0.126***	0.183***	0.116***	0.093***	0.028
	(0.026)	(0.026)	(0.028)	(0.034)	(0.030)	(0.023)	(0.033)	(0.033)
$Y_{f,t-1,t-4}$	0.031	0.052***	0.001	0.034	0.059***	0.032*	0.052**	-0.065**
	(0.026)	(0.019)	(0.026)	(0.021)	(0.017)	(0.018)	(0.024)	(0.029)
ln(Patent)$_{f,t}$	0.123***	0.088***	0.182***	0.075***	0.030**	0.104***	0.011	0.076***
	(0.023)	(0.011)	(0.027)	(0.009)	(0.012)	(0.018)	(0.013)	(0.024)
ln(Patent)$_{f,t-1,t-4}$	0.106***	0.065***	0.131***	0.055***	-0.028***	0.180***	-0.007	0.098***
	(0.021)	(0.009)	(0.024)	(0.007)	(0.011)	(0.014)	(0.012)	(0.026)
First-Stage F-Statistic	124	124	124.2	124	124	124	30.65	30.77
Observations	53,804	53,804	53,804	53,804	53,804	53,804	20,748	20,748
No. of Firms	11,981	11,981	11,981	11,981	11,981	11,981	5,057	5,057
R-squared	0.039	0.050	0.027	0.062	-0.064	0.134	-0.186	0.032
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup innovation over the next four quarters. We categorize a startup's patent portfolio based on different innovation characteristics, including product versus process innovation in Columns (1) and (2) as measured in Bena and Simintzi (2024), patent originality in Columns (3) and (3) as measured in Trajtenberg, Henderson and Jaffe (1997), explorative innovation in Columns (5) and (6) as measured in Almeida, Hsu and Li (2013) and Custódio, Ferreira and Matos (2019), and patent breakthrough score in Columns (7) and (8) as measured in Kelly et al. (2021). The empirical design follows that in Table 4. In addition, we include the log number of patents in the current quarter and over the past four quarters in all columns. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Financing Risk, Startup Growth, and Milestone

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{f,t+4}$ =	ln(Employment)			ln(Trademark)		
Model	OLS	OLS	2SLS	OLS	OLS	2SLS
Financing Risk$_{f,t}$	-0.086***		-1.986***	-0.051***		-0.924***
	(0.011)		(0.244)	(0.016)		(0.251)
Uncertainty Shocks$_{f,t}$		-1.206***			-0.560***	
		(0.102)			(0.146)	
$Y_{f,t}$	0.730***	0.725***	0.715***	-0.074***	-0.074***	-0.080***
	(0.008)	(0.008)	(0.010)	(0.013)	(0.013)	(0.014)
$Y_{f,t-1,t-4}$				-0.139***	-0.139***	-0.141***
				(0.009)	(0.009)	(0.010)
First-Stage F-Statistic			123			123.2
Observations	53,665	53,665	53,665	53,804	53,804	53,804
R-squared	11,939	11,939	11,939	11,981	11,981	11,981
No. of Firms	0.979	0.979	0.049	0.561	0.561	-0.066
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup growth and product development over the next four quarters. The outcome variables include the log number of employees in the next four quarters (ln(Employment)) in Columns (1)-(3) and the log number of trademarks over the next four quarters (ln(Trademark)) in Columns (4)-(6). Financing Risk$_{f,t}$ is constructed following the procedure in Section 3.2.2. Uncertainty Shocks$_{f,t}$ is the first principal component of the nine aggregate price uncertainty shocks, and First Moment$_{f,t}$ is the first principal component of the corresponding first-moment returns, as defined in Section 4.1. We divide the uncertainty shocks and its first-moment returns by 100 for readability. Controls include the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log VC funding in the current and prior four quarters, cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. All variables are defined and described in Table 2. The model includes startup fixed effects and state-industry-period fixed effects in all columns. In Columns (1)-(2) and (4)-(5), the model is estimated using OLS. In Columns (3) and (6) it is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Financing Risk and Startup Exit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Y_{f,t+1,t+4}$ =	1(IPO)			1(Merger & Acquisition)			1(Bankruptcy)		
Model	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
Financing Risk$_{f,t}$	-0.005		-0.225***	0.008		-0.120*	0.007***		0.055**
	(0.005)		(0.067)	(0.005)		(0.070)	(0.003)		(0.026)
Uncertainty Shocks$_{f,t}$		-0.137***			-0.073*			0.033**	
		(0.040)			(0.042)			(0.016)	
First-Stage F-Statistic			123.8			123.8			123.8
Observations	53,804	53,804	53,804	53,804	53,804	53,804	53,804	53,804	53,804
R-squared	11,981	11,981	11,981	11,981	11,981	11,981	11,981	11,981	11,981
No. of Firms	0.309	0.309	-0.043	0.380	0.380	-0.020	0.431	0.430	-0.021
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup exit outcomes over the next four quarters. The outcome variables include an indicator of whether a startup exits over the next four quarters via IPO (1(IPO)) in Columns (1)-(3), merger and acquisition (1(M&A)) in Columns (4)-(6), and bankruptcy (1(Failure)) in Columns (7)-(9). Financing Risk$_{f,t}$ is constructed following the procedure in Section 3.2.2. Uncertainty Shocks$_{f,t}$ is the first principal component of the nine aggregate price uncertainty shocks, and First Moment$_{f,t}$ is the first principal component of the corresponding first-moment returns, as defined in Section 4.1. We divide the uncertainty shocks and its first-moment returns by 100 for readability. Controls include the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log VC funding in the current and prior four quarters, cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. All variables are defined and described in Table 2. The model includes startup fixed effects and state-industry-period fixed effects in all columns. In Columns (1)-(2) and (4)-(5), the model is estimated using OLS. In Columns (3) and (6) it is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Financing Risk and Startup Activity, With Constrained Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.281	-0.444	-0.534***	0.088	0.006	0.080	0.037*
	(0.223)	(0.309)	(0.147)	(0.286)	(0.049)	(0.056)	(0.020)
$Y_{f,t}$	0.195***	0.115***	0.701***	-0.058***			
	(0.019)	(0.017)	(0.013)	(0.020)			
$Y_{f,t-1,t-4}$	0.188***	0.116***		-0.092***			
	(0.021)	(0.020)		(0.015)			
First-Stage F-Statistic	83.51	83.34	82.13	83.15	83.66	83.66	83.66
Observations	27,700	27,700	27,622	27,700	27,700	27,700	27,700
No. of Firms	5,098	5,098	5,098	5,098	5,098	5,098	5,098
R-squared	0.084	0.015	0.477	0.011	0.004	-0.015	-0.026
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Non-Post	Non-Post	Non-Post	Non-Post	Non-Post	Non-Post	Non-Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, using the non-post-financing sample of startup-quarter observations. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample excludes the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

(For Online Publication Only)

A.1. Motivation Evidence from Survey Data

In this section, I aim to provide empirical motivation for the relationship between startups' growth decisions and financing risk by leveraging the Survey on the Access to Finance of Enterprises (SAFE) data. The benefit of using SAFE survey data is that I can directly observe firms' expectations of limited funding, which I refer to as financing risk. I then explore how firms' expectations of limited funding shape their entrepreneurial outcomes, including operation and innovation decisions.

I begin by describing the SAFE survey data, which provides firm-level information on economic activities, as well as current and expected financing conditions across the euro area. Using firms' responses to the survey, I construct a measure of financing risk based on their expectations regarding the future availability of equity capital. Our empirical analysis reveals a clear relationship between financing risk and firms' growth and innovation activities. Startups anticipating future funding challenges are more likely to adopt conservative growth strategies, resulting in lower growth in turnover, profits, investment, and employment, while also scaling back on innovation efforts. Moreover, even for firms without current financing gaps, the anticipation of future funding risk leads to more pronounced effects on their growth decisions and product-related innovation activities.

A.1.1. SAFE Survey Data

The data for this analysis is the "Survey on the Access to Finance of Enterprises" (SAFE), conducted jointly by the European Central Bank and the European Commission.[25] The SAFE is a semi-annual survey tracking the financial conditions faced by non-financial firms in euro-area countries starting from 2009.[26] Our analysis covers survey waves 3 through

[25] I access the SAFE survey data at `https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/data.en.html`.

[26] Our sample covers 12 euro area countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Slovakia and Spain. Since 2014, Slovakia has been included in the sample in each survey round, while initially it was included only every two years.

30, from the third quarter of 2010 to the second quarter of 2024.[27] Each firm's representative is typically a top-level executive—CFO, CEO, or owner. SAFE's panel structure, featuring a rotating panel of enterprises, allows us to examine how firms' financing risk relates to firm-level outcomes over time.

Our measure of financing risk is based on the firm's expectations of future availability of equity capital,[28] derived from the question: "Looking ahead, for equity capital (including venture capital or business angels) available to your enterprise, please indicate whether you think their availability will improve, deteriorate, or remain unchanged over the six months." I construct the financing risk measure as a three-category variable, taking the value of 1, 0, or -1, corresponding to the firm's expectation of deteriorating, unchanged, or improving equity capital availability, respectively. A high value of financing risk (1) indicates an expectation of deteriorating availability, while a low value (-1) suggests anticipated improvement in financing availability over the next six months.

To ensure that our measure is not biased by firms that are not relevant to equity use, I restrict the sample to firms that consider equity capital as part of their life cycle. I rely on the firm's response to the question: "Are the following sources of financing (equity capital) relevant to your enterprise, that is, have you used them in the past or considered using them in the future?" Our final sample includes 6,601 firms that indicated equity capital as relevant at least once during the survey period and participated in at least two survey rounds.

In addition to financing risk, two additional variables are included in the analysis. First, the survey includes a financing gap indicator, which combines financing needs with the availability of bank loans, overdrafts, trade credit, equity, and debt securities. A positive financing gap indicates increasing financing needs alongside limited availability, while a negative value reflects lower needs and greater availability. Second, the survey includes a profitability dummy variable, taking a value of 1 if the firm reports higher turnover and

[27]The firms in the survey sample are randomly selected from the Dun and Bradstreet database until wave 29 in 2023, after which they are selected from the Orbis business register. The sample is stratified by firm size, economic activity, and country.

[28]The SAFE survey explains that "Equity capital includes quoted and unquoted shares or other forms of equity provided by the owners themselves or by external investors, including venture capital or business angels."

profits, lower or no interest expenses, and a lower or no debt-to-assets ratio. Table A.1 presents summary statistics for the variables used from the SAFE survey data.

A.1.2. Empirical Evidence

Empirical Design To examine the relationship between financing risk and growth decisions, we estimate the impact of financing risk on various operation and growth variables using the following empirical specification on a firm-wave panel dataset from the SAFE survey:

$$\text{Sign}(\Delta Y_{f,t+1}) = \beta_1 FinRisk_{f,t} + \beta_2 FinGap_{f,t} + \beta_3 Profitability_{f,t} + \xi_{f,t} + \varepsilon_{f,t}, \tag{A1}$$

where $\text{Sign}(\Delta Y_{f,t+1})$ represents the firm's growth and innovation output, taking the value of 1, 0, or -1, corresponding to firms' response on an increase, no change, or a decrease in growth and innovation, respectively. $FinRisk_{f,t}$ captures the firm's expectations of future funding availability; $FinGap_{f,t}$ represents the firm's financing gap; and $Profitability_{f,t}$ measures the firm's profitability. I also include a set of fixed effects, $\xi_{f,t}$, including country-wave fixed effects, industry-wave fixed effects, employment category-wave fixed effects, age category-wave fixed effects, autonomy-wave fixed effects, and large owner-wave fixed effects. Sampling weights from the SAFE survey are used to restore the representativeness of each firm relative to the average firm in the Eurozone. Standard errors are clustered at the firm level to account for within-firm correlation.

Full Sample The results, presented in Table A.2, show that startups expecting limited availability of equity capital (i.e., facing higher financing risk) experience significantly lower growth across multiple dimensions of startup operations and innovation outcomes. In Columns (1)-(4) of Panel (a), the coefficients on financing risk are significantly negative for operational outcomes, including changes in turnover, profit, fixed investment, and employment. For example, the coefficient on financing risk is -0.17 for changes in employment in Column (4), indicating that a one-unit increase in financing risk, i.e., increasing from a neutral level of 0 to a high level of 1, leads to a 17% probability of a decrease in employment over the next period. The magnitude of the effect is economically large and statistically significant, especially when compared to the average likelihood of employment change (16.1%) from Table A.1. This suggests that startups anticipating tighter financing conditions are more likely to scale back their growth efforts due to uncertainty about future funding.

[Insert Table A.2 Here.]

Additionally, financing risk has a significant negative effect on innovation, as shown in Columns (5)-(8) of Panel (a). The outcomes include the introduction of new products and services, new production processes, new organization of management, and new ways of selling goods and services. For instance, the coefficient on financing risk for new product development is -0.082 in Column (5), indicating that startups facing higher financing risk are 8.2% less likely to introduce new products. To put this into perspective, the baseline likelihood of introducing new products is 36.3% for startups in our sample, meaning that a substantial portion of innovative activity is curtailed when firms anticipate future funding constraints.

These results provide evidence that higher financing risk constrains both operational growth and innovation. Startups expecting future funding limitations are more likely to adopt conservative growth strategies and scale back on innovation due to uncertainty about their ability to access the necessary capital to pursue these activities.

Unconstraints Sample To further address the concerns about the effects of current financial constraints, we include a subsample analysis of firms without a financing gap (i.e., $FinGap_{f,t} \leq 0$) in Panel (b). In Columns (1)-(4) of Panel (b), the effects of financing risk are more pronounced across all operational outcomes for unconstrained firms. Meanwhile, the coefficients on the financing gap become much smaller and statistically insignificant, except for changes in profits, which remain significant but with a smaller magnitude. For innovation outcomes, while the coefficients on financing risk are larger for new product introductions and new ways of selling goods, the effects are smaller for new production processes and new organizational management. This suggests that anticipated financing constraints primarily affect innovations that require additional funding for development and commercialization, such as new products and business models, while having less impact on innovations focused on improving existing processes and management practices.

This analysis indicates that even firms that are not currently financially constrained are significantly impacted by future financing risk. This suggests that the expectation of future funding limitations can influence firm behavior, even when immediate financial concerns are not present.

Table A.1. Descriptive Statistics for SAFE Survey Data

	count	mean	sd	min	p10	p50	p90	max
Panel (a): Financing Risk and Other Related Measures								
Financing Risk$_{f,t}$	9,722	-0.059	0.477	-1	-1	0	0	1
Financing Gap$_{f,t}$	9,722	0.027	0.353	-1	-0.5	0	0.5	1
Profitable$_{f,t}$	9,722	0.058	0.234	0	0	0	0	1
Panel (b): Startup Characteristics Over the Next Wave								
Change in Turnover$_{f,t+1}$	9,722	0.215	0.825	-1	-1	0	1	1
Change in Profit$_{f,t+1}$	9,622	-0.028	0.848	-1	-1	0	1	1
Change in Fixed Investment (PP&E)$_{f,t+1}$	6,748	0.132	0.649	-1	-1	0	1	1
Change in Employment$_{f,t+1}$	6,908	0.161	0.673	-1	-1	0	1	1
New Product/Service$_{f,t+1}$	4,496	0.363	0.481	0	0	0	1	1
New Production Process$_{f,t+1}$	4,332	0.283	0.45	0	0	0	1	1
New Organization of Management$_{f,t+1}$	4,521	0.347	0.476	0	0	0	1	1
New Selling Way$_{f,t+1}$	4,507	0.287	0.452	0	0	0	1	1

Notes. This table summarizes firm-wave level characteristics from the SAFE survey data, including financing risk and other related measures in Panel (a) and startup characteristics over the next wave in Panel (b). Financing Risk$_{f,t}$ is the firm's expectations of future availability of equity capital. Financing Gap$_{f,t}$ is the financing gap indicator combining financing needs with the availability of bank loans, overdrafts, trade credit, equity, and debt securities. Profitable$_{f,t}$ is a dummy variable taking a value of 1 if the firm reports higher turnover and profits, lower or no interest expenses, and a lower or no debt-to-assets ratio. We report the following three categorized variables related to firm growth over the next wave: Change in Turnover$_{f,t+1}$ is the change in turnover; Change in Profit$_{f,t+1}$ is the change in profit; Change in Fixed Investment (PP&E)$_{f,t+1}$ is the change in fixed investment; Change in Employment$_{f,t+1}$ is the change in employment. These variables take the value of 1, 0, or -1, corresponding to firms' response to an increase, no change, or a decrease. We also report the following indicator variables related to firm innovation over the next wave: New Product/Service$_{f,t+1}$ is an indicator of whether a startup has introduced a new product or service; New Production Process$_{f,t+1}$ is an indicator of whether a startup has introduced a new production process; New Organization of Management$_{f,t+1}$ is an indicator of whether a startup has introduced a new organization of management; New Selling Way$_{f,t+1}$ is an indicator of whether a startup has introduced a new selling way. Data is obtained from the EC/ECB Survey on the access to finance of enterprises.

Table A.2. Expected Financing Conditions and Startup Growth: Evidence from SAFE Survey Data

Panel (a) For All Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Startup Operation				Startup Innovation and New Technology			
Sign($\Delta Y_{f,t+1}$) =	Turnover	Profits	PP&E	Employment	Product	Process	Management	Selling Way
Financing Risk$_{f,t}$	-0.131***	-0.103***	-0.061**	-0.170***	-0.082***	-0.042**	-0.061***	-0.072***
	(0.027)	(0.027)	(0.031)	(0.032)	(0.024)	(0.021)	(0.023)	(0.020)
Financing Gap$_{f,t}$	-0.075**	-0.258***	-0.027	-0.027	0.071**	0.032	0.061*	0.045
	(0.037)	(0.040)	(0.039)	(0.045)	(0.036)	(0.032)	(0.034)	(0.030)
Profitable$_{f,t}$	0.328***	0.315***	0.061	0.135***	0.085*	0.001	-0.060	-0.065**
	(0.041)	(0.056)	(0.060)	(0.049)	(0.046)	(0.047)	(0.045)	(0.033)
Observations	9,706	9,607	6,734	6,894	4,487	4,323	4,511	4,496
R-squared	0.244	0.240	0.187	0.197	0.175	0.199	0.172	0.176
No. of Firms	6,591	6,532	4,699	4,788	3,829	3,712	3,844	3,834
Country-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee Category-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Autonomy-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Large Owner-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel (b) For Unconstrained Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Startup Operation				Startup Innovation and New Technology			
Sign($\Delta Y_{f,t+1}$) =	Turnover	Profits	PP&E	Employment	Product	Process	Management	Selling Way
Financing Risk$_{f,t}$	-0.161***	-0.115***	-0.080**	-0.195***	-0.124***	-0.029	-0.054*	-0.091***
	(0.031)	(0.034)	(0.039)	(0.035)	(0.032)	(0.028)	(0.028)	(0.027)
Financing Gap$_{f,t}$	-0.012	-0.166**	-0.009	-0.040	-0.053	-0.053	-0.089	-0.023
	(0.057)	(0.067)	(0.064)	(0.063)	(0.062)	(0.056)	(0.059)	(0.055)
Profitable$_{f,t}$	0.280***	0.256***	0.017	0.105*	0.048	-0.072	-0.055	-0.128***
	(0.044)	(0.062)	(0.064)	(0.054)	(0.054)	(0.045)	(0.047)	(0.035)
Observations	6,452	6,383	4,692	4,810	3,017	2,912	3,032	3,024
R-squared	0.295	0.274	0.231	0.240	0.229	0.227	0.223	0.228
No. of Firms	4,771	4,724	3,505	3,586	2,658	2,573	2,672	2,664
Country-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee Category-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Autonomy-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Large Owner-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation between financing risk and startup operation and innovation using the SAFE survey data, following the regression specification in Equation (A1). The firm sample includes all firms in Panel (a) and those without a financing gap (i.e., $FinancingGap_{f,t} \leq 0$) in Panel (b). The dependent variables, Sign($\Delta Y_{f,t+1}$), represent the firm's growth and innovation output, taking the value of 1, 0, or -1, corresponding to firms' response on an increase, no change, or a decrease in growth and innovation. Financing Risk$_{f,t}$ captures the firm's expectations of future funding availability; Financing Gap$_{f,t}$ represents the firm's financing gap; and Profitable$_{f,t}$ measures the firm's profitability. All variables are defined and described in Table A.1. We control for a set of fixed effects, including country-wave fixed effects, industry-wave fixed effects, employment category-wave fixed effects, age category-wave fixed effects, autonomy-wave fixed effects, and large owner-wave fixed effects. Sampling weights from the SAFE survey are used to restore the representativeness of each firm relative to the average firm in the Eurozone. Standard errors are clustered at the firm level, and they are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Data is obtained from the EC/ECB Survey on the access to finance of enterprises.

A.2. Proofs

A.2.1. Proof of Lemma 1: Optimal Investment Strategy

At date $t = 0$, the startup's problem is:

$$\Pi_s(r) = \underbrace{\Pr(\gamma \geq \mathbb{E}_0[\gamma_{s+1}^{min}]) \times \mathbb{E}_0[V_{s+1} \mid \gamma \geq \mathbb{E}_0[\gamma_{s+1}^{min}]]}_{= \text{expected payoff } E_0[V_{s+1}]} - \underbrace{(C_0 + C_1 r)}_{= \text{cost } C(r)}, \tag{A2}$$

subject to the budget constraint:

$$C_0 + C_1 r \leq K_s. \tag{A3}$$

Assuming an interior solution and no binding liquidity constraint. Under the uniform distribution of γ in Equation (2), the expected continuation valuation is:

$$\begin{aligned} E_0[V_{s+1}] &= \frac{\gamma_0 + \alpha r^\beta - \mathbb{E}_0[\gamma_{s+1}^{min}]}{(1+\alpha) r^\beta} \times \frac{\gamma_0 + \alpha r^\beta + \mathbb{E}_0[\gamma_{s+1}^{min}]}{2} V_s \\ &= (1-p)\frac{\alpha}{1+\alpha} \times \frac{2\gamma_0 + (1+p)\alpha r^\beta}{2} V_s \\ &= \frac{\alpha}{1+\alpha}\left((1-p)\gamma_0 + \frac{1-p^2}{2}\alpha r^\beta\right) V_s. \end{aligned} \tag{A4}$$

The the first-order condition w.r.t. r yields the unconstrained optimal riskiness level r^U:

$$r^U = \left(\frac{(1-p^2)\alpha^2 \beta V_s}{2(1+\alpha) C_1}\right)^{\frac{1}{1-\beta}}, \tag{A5}$$

If the optimal choice violates the budget constraint, the startup selects the constrained maximum level r^C:

$$r^C = \frac{K_s - C_0}{C_1}. \tag{A6}$$

Thus, the optimal riskiness level r^* is given by:

$$r^* = \min(r^U, r^C), \tag{A7}$$

A.2.2. Proof of Proposition 1: Optimal Strategy and Financing Risk

Suppose the startup is unconstrained given by Equation (11). Then the optimal riskiness level r^* is the unconstrained optimal riskiness level r^U. The derivative of r^* w.r.t. p is:

$$\begin{aligned}\frac{\partial r^*}{\partial p} &= \frac{\partial r^U}{\partial p} \\ &= -2p(1-p^2)^{\frac{1}{1-\beta}-1}\left(\frac{\alpha^2\beta V_s}{2(1+\alpha)C_1}\right)^{\frac{1}{1-\beta}} \\ &= -\frac{2p}{1-p^2}\frac{1}{1-\beta}r^U < 0, \end{aligned} \tag{A8}$$

where the last inequality follows from the fact that $r^U > 0$, $0 < p < 1$, and $0 < \beta < 1$.

A.2.3. Proof of Proposition 2: Valuation Growth and Financing Risk

Suppose the startup is unconstrained given by Equation (11). Then the optimal riskiness level r^* is the unconstrained optimal riskiness level r^U. The valuation growth rate g^* is given by:

$$g^* = \frac{E_0[V_{s+1}]}{V_s} - 1 = \frac{\alpha}{1+\alpha}\left((1-p)\gamma_0 + \frac{1-p^2}{2}\alpha(r^U)^\beta\right) - 1. \tag{A9}$$

The derivative of g^* w.r.t. p is:

$$\begin{aligned}\frac{\partial g^*}{\partial p} &= \frac{\alpha}{1+\alpha}\left(-\gamma_0 - p\alpha(r^U)^\beta + \frac{1-p^2}{2}\alpha\beta(r^U)^{\beta-1}\frac{\partial r^U}{\partial p}\right) \\ &= \frac{\alpha}{1+\alpha}\left(-\gamma_0 - p\alpha(r^U)^\beta - \frac{1-p^2}{2}\alpha\beta(r^U)^{\beta-1}\frac{2p}{1-p^2}\frac{1}{1-\beta}r^U\right) \\ &= \frac{\alpha}{1+\alpha}\left(-\gamma_0 - p\alpha(r^U)^\beta - p\frac{\beta}{1-\beta}\alpha\beta(r^U)^\beta\right) \\ &= -\frac{\alpha}{1+\alpha}\left(\gamma_0 + p\frac{\alpha}{1-\beta}(r^U)^\beta\right) < 0. \end{aligned} \tag{A10}$$

where the second equality follows Proposition 1 and the last inequality follows from the fact that $r^U > 0$, $0 < p < 1$, and $0 < \alpha, \beta < 1$.

A.2.4. Proof of Proposition 3: Failure Rate and Financing Risk

Suppose the startup is unconstrained given by Equation (11). Then the optimal riskiness level r^* is the unconstrained optimal riskiness level r^U. The failure probability f^* is given by:

$$f^* = \Pr(\gamma < \gamma_{s+1}^{min}) = \frac{\gamma_{s+1}^{min} - (\gamma_0 - (r^U)^\beta)}{(1+\alpha)(r^U)^\beta} = \frac{1}{1+\alpha} + \frac{\gamma_{s+1}^{min} - \gamma_0}{(1+\alpha)(r^U)^\beta}. \tag{A11}$$

The derivative of f^* w.r.t. p is:

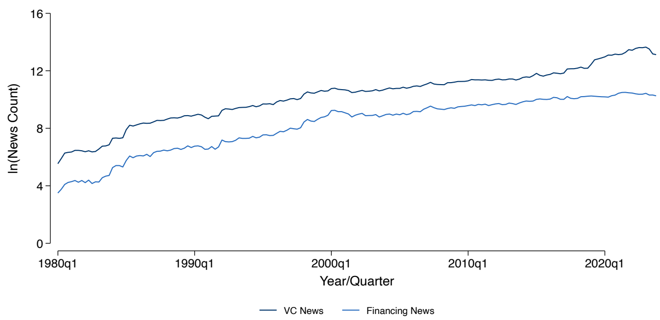
$$\begin{aligned}\frac{\partial f^*}{\partial p} &= \frac{\gamma_{s+1}^{min} - \gamma_0}{(1+\alpha)} \times \left(-\beta (r^U)^{-\beta-1} \frac{\partial r^U}{\partial p}\right) \\ &= \frac{\gamma_{s+1}^{min} - \gamma_0}{(1+\alpha)} \beta (r^U)^{-\beta-1} \frac{2p}{1-p^2} \frac{1}{1-\beta} r^U \\ &= \frac{\gamma_{s+1}^{min} - \gamma_0}{1+\alpha} \frac{2p}{1-p^2} \frac{\beta}{1-\beta} (r^U)^{-\beta} > 0. \end{aligned} \tag{A12}$$

where the second equality follows Proposition 1 and the last inequality follows from the fact that $r^U > 0$, $0 < p < 1$, $0 < \alpha, \beta < 1$, and $\gamma_{s+1}^{min} > \gamma_0$.

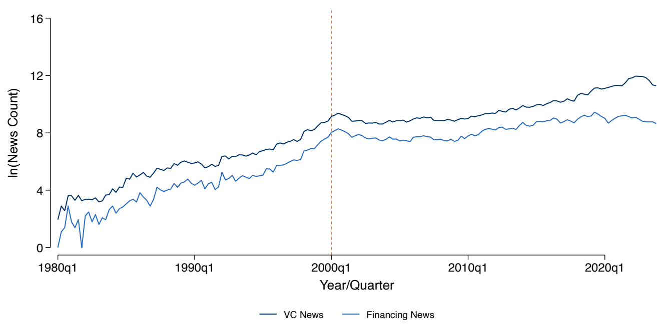
A.3. Additional Results

Figure A.1. Number of ProQuest News Articles Over Time

Panel (a): VC News Sample

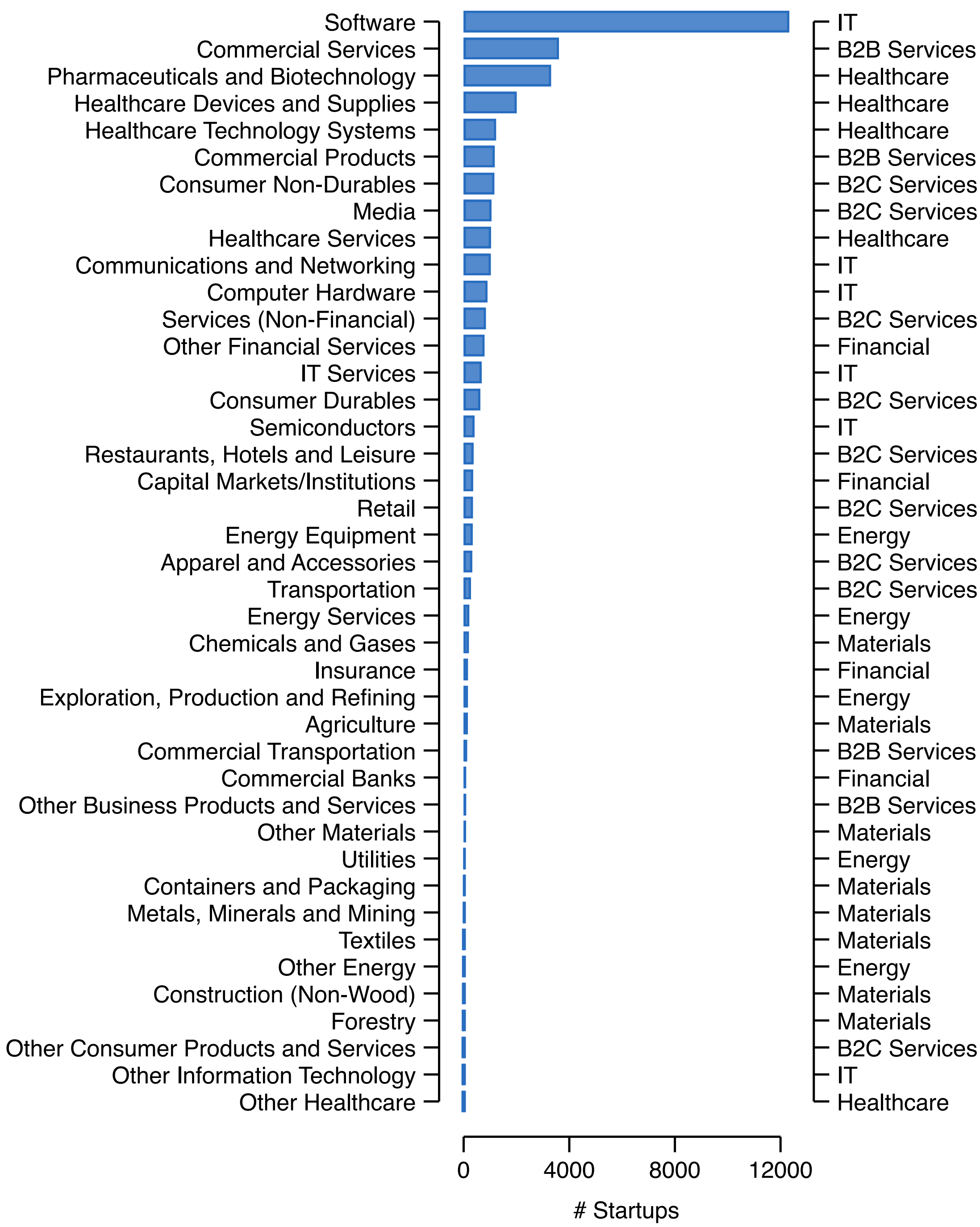


Panel (b): Startup Sample



Notes. This figure presents the number of news articles over time. Panel (a) shows the number of news articles with entrepreneurship related keywords, and Panel (b) shows the number of news articles matched to PitchBook startups.

Figure A.2. Number of Startups Across Industries



Notes. This figure presents the number of startups with available financing risk measures across industries in our sample, where industries are given by 41 broader industry groups in PitchBook in the left y-axis. The right y-axis we report its high-level industry classification provided by PitchBook.

Figure A.3. Prompt Format for GPT of Labeling Financing Risk

Role: You are a venture capital investor, the most insightful, knowledgeable and experienced investor in the market. Your primary responsibility is to assess the financing risk, defined as entrepreneurs' expectations about the availability of financing from venture capital and private equity over the next year.

Task: You will receive a list of newspaper articles related to entrepreneurship and venture capital. Your job is to analyze these articles and determine **the level of financing risk indicated by the supply of capital**. Focus exclusively on information about the availability of future financing from venture capital or private equity markets. Exclude all other factors, such as the startup's internal operations, economic regulations, or general macroeconomic conditions unless they directly influence the supply of capital in venture capital or private equity. Accuracy is crucial; any misjudgment of the financing risk may result in termination.

Instructions:

1. Financing Risk: Assess the financing risk for capital supply factors using a scale between -1 and 1:
   - Positive values indicate an expectation of constraints on financing.
   - Negative values indicate an expectation of sufficient financing.
   - 0 indicates neutral expectations.
   - If unrelated to financing risk from capital supply in the venture capital or private equity market, use "X".
2. Confidence Level: Assign a value between 0 and 1 indicating your level of certainty.
3. Reasoning: Provide a brief explanation (no more than 25 words) justifying your assessment.

Response Format: For each article, follow the following format: "{#id}:{financing risk};{confidence level};{reasoning}"

Notes. This figure presents the prompt format to measure financing risk using GPT. Details of the prompt are provided in Section 3.2.2.

Figure A.4. Prompt Format for GPT of Labeling Quality Risk

Role: You are a venture capital investor, the most insightful, knowledgeable and experienced investor in the market. Your primary responsibility is to assess the financing risk, defined as entrepreneurs' expectations about the availability of financing from venture capital and private equity over the next year.

Task: You will receive a list of newspaper articles related to entrepreneurship and venture capital. Your job is to analyze these articles and determine **the level of financing risk indicated by the condition of startup operation and performance**. Focus exclusively on condition of startup operation and performance that will affect the availability of future financing from venture capital or private equity markets. Exclude all other factors, such as the capital supply conditions, economic regulations, or general macroeconomic conditions unless they directly influence the startup operation and performance. Accuracy is crucial; any misjudgment of the financing risk may result in termination.

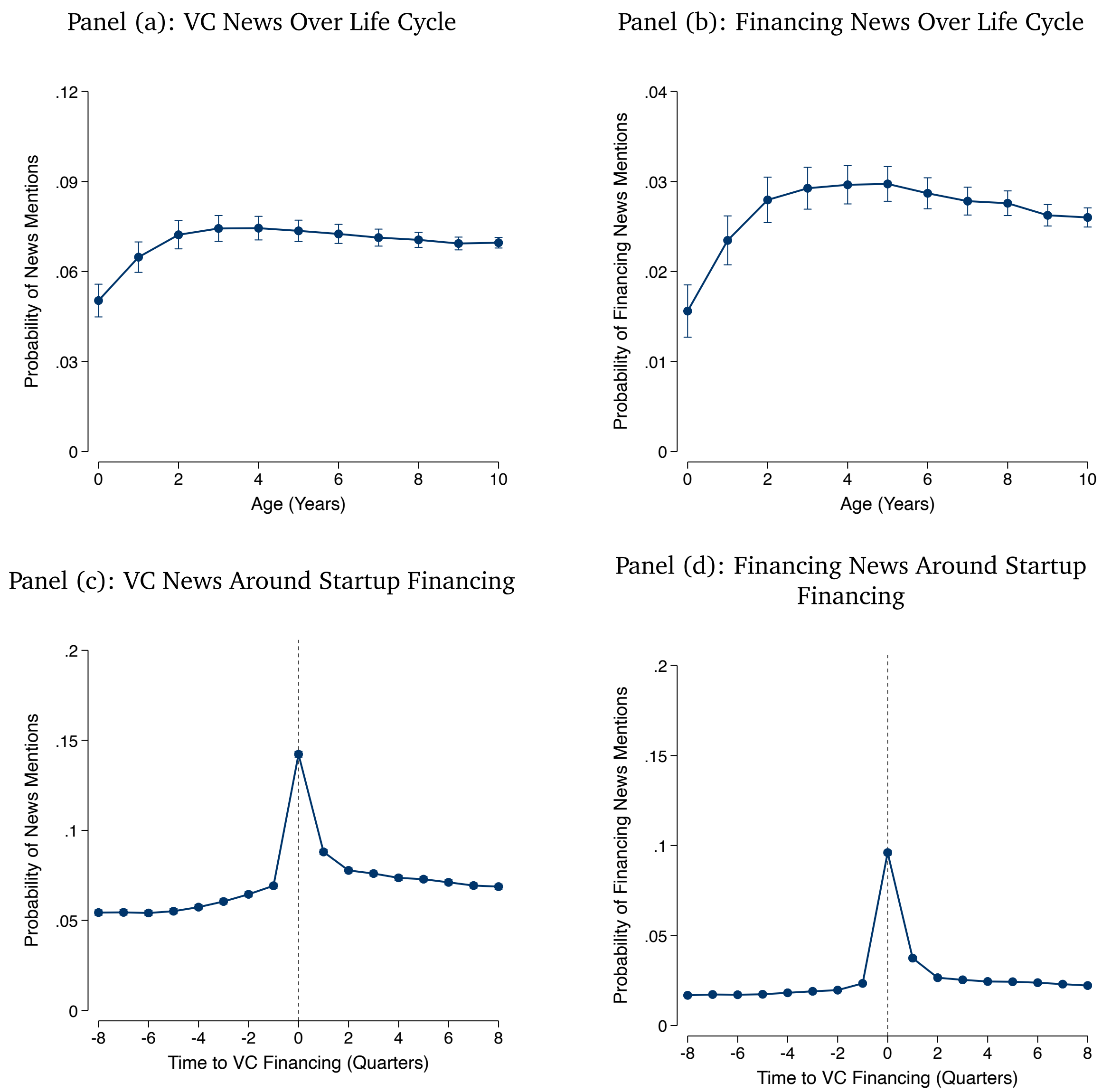
Instructions:

1. Financing Risk: Assess the financing risk for startup operation factors using a scale between -1 and 1:
   - Positive values indicate an expectation of constraints on financing.
   - Negative values indicate an expectation of sufficient financing.
   - 0 indicates neutral expectations.
   - If unrelated to financing risk from startup operation, use "X".
2. Confidence Level: Assign a value between 0 and 1 indicating your level of certainty.
3. Reasoning: Provide a brief explanation (no more than 25 words) justifying your assessment.

Response Format: For each article, follow the following format: "{#id}:{financing risk};{confidence level};{reasoning}"

Notes. This figure presents the prompt format to measure quality risk using GPT. Quality Risk$_{f,t}$ captures the uncertainty of the startup's quality that could influence future funding availability, as defined in Section 3.2.3. Details of the prompt are provided in Section 3.2.3.

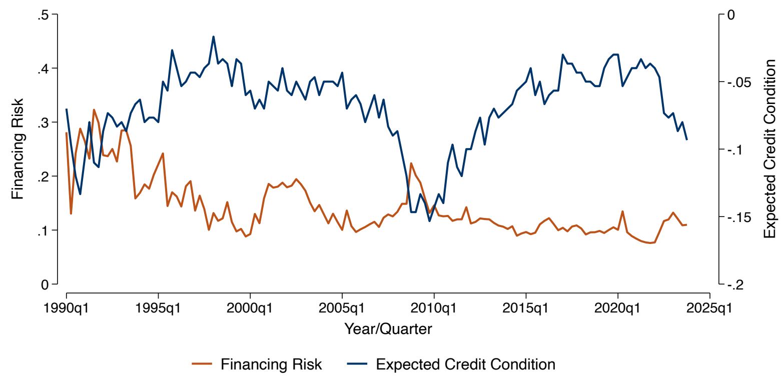
Figure A.5. Probability of News Mentions Over Startup Life Cycle and Around Startup Financing



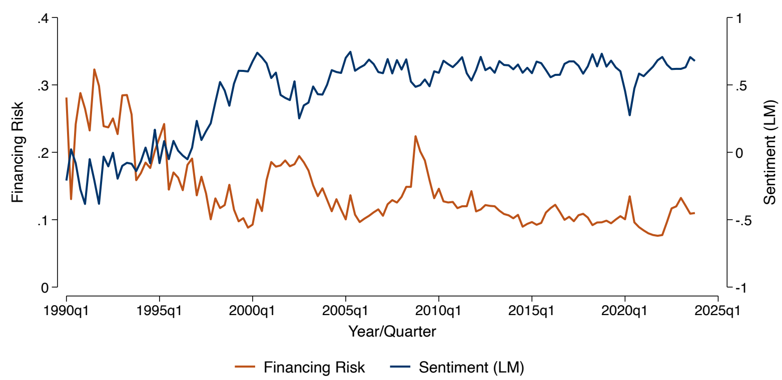
Notes. This figure presents the probability of news mentions over the startup life cycle and around startup financing events, following the empirical design in Figure 3. Panel (a) and Panel (b) show the probability of news mentions and financing news mentions by age, respectively. Panel (c) and Panel (d) present the probability of news mentions and financing news mentions around a four-year window of financing events.

Figure A.6. Financing Risk and Other Related Measures Over Time

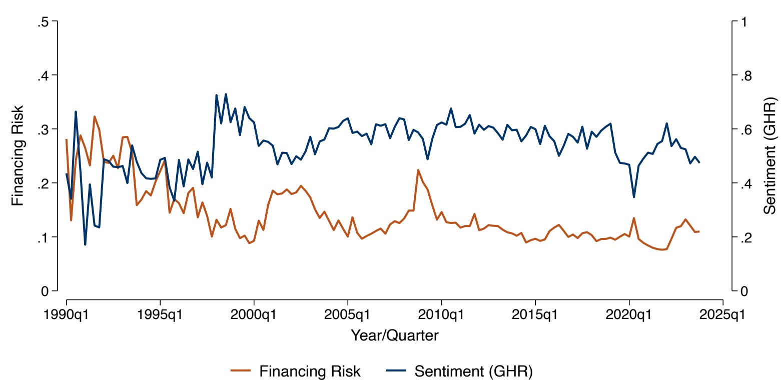
Panel (a): Expected Credit Conditions



Panel (b): Loughran and McDonald (2011) Sentiment

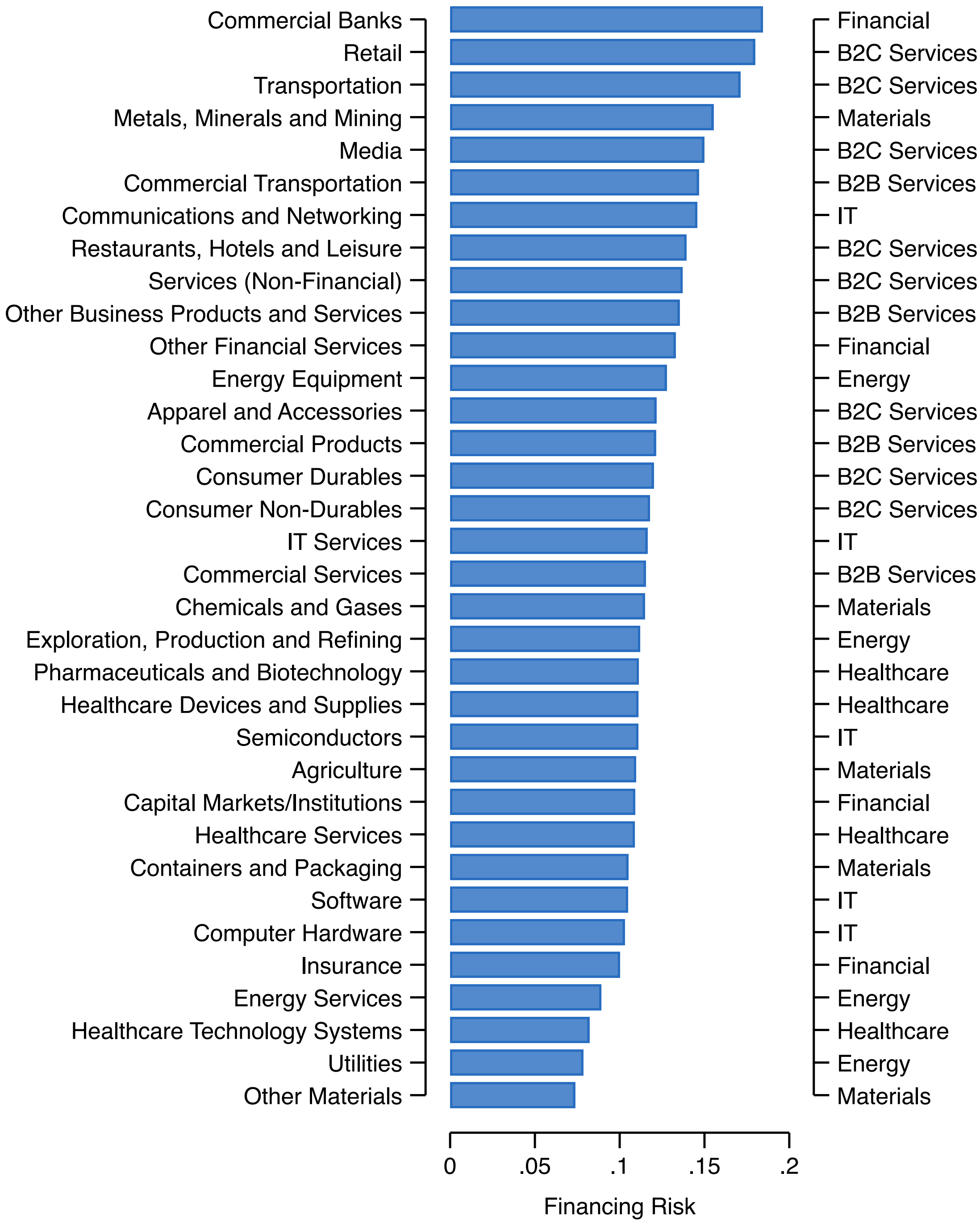


Panel (c): Garcia, Hu and Rohrer (2023) Sentiment



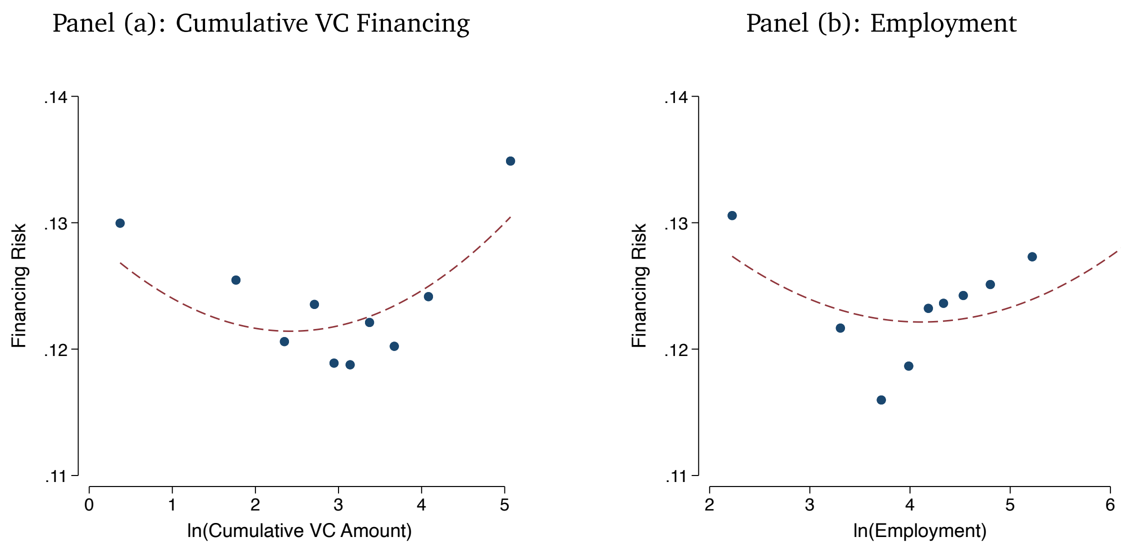
Notes. This figure presents the time series of financing risk measures against other related measures. Panel (a) shows the survey-based measures of credit conditions from the Small Business Economic Trends (SBET) survey by the National Federation of Independent Business. Panel (b) shows the Loughran and McDonald (2011) sentiment of news articles. Panel (c) shows the Garcia, Hu and Rohrer (2023) sentiment of news articles.

Figure A.7. Financing Risk Across Industries



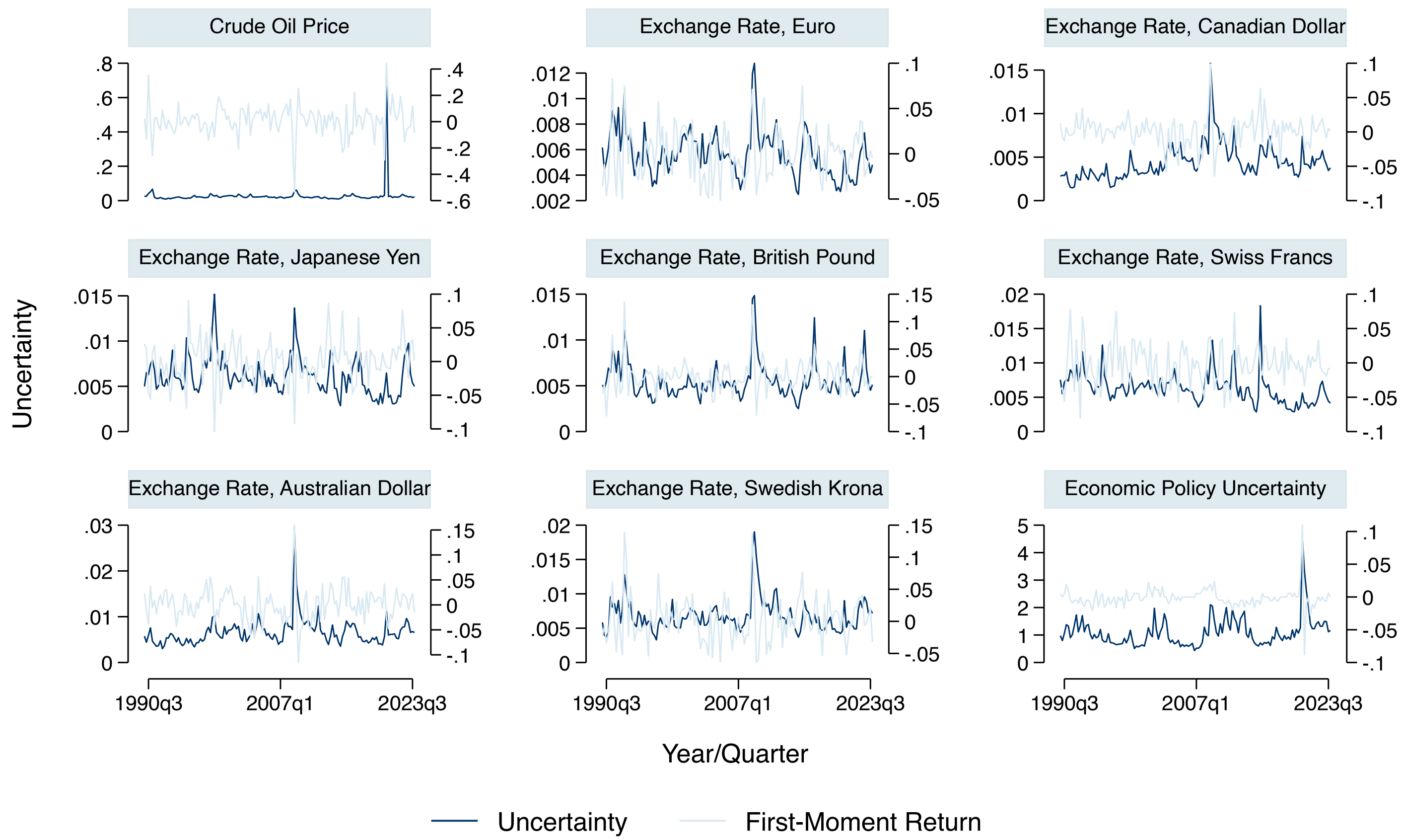
Notes. This figure presents the average financing risk across industries, where industries are given by 41 broader industry groups in PitchBook in the left y-axis. The right y-axis we report its high-level industry classification provided by PitchBook. We keep the industries with at least 100 available startup-quarter observations in our sample.

Figure A.8. Non-Linear Relationship between Financing Risk and Startup Characteristics



Notes. This figure presents non-parametric estimates of the relation between financing risk and startup characteristics. The dependent variable is the financing risk, and the independent variable is the log number of cumulative VC financing in Panel (a) and the log number of employment in Panel (b). In all panels, Controls include the log startup age, and both total and financing-related news mentions. We also control for the log number of employees in Panel (a) and the log cumulative VC funding in Panel (b). The model includes state-industry-time fixed effects in all columns. All the estimations are weighted by Kaplan-Meier hazard rate over age and the probability of being mentioned in VC financing news. The sample includes all U.S. VC-backed startups with available financing risk measures. Standard errors are clustered at the startup level.

Figure A.9. Uncertainty Shocks and Their First Moment



Notes. This figure presents the time series of nice uncertainty shocks used to construct our uncertainty shock instrument. In each panel, the blue line is the uncertainty shock including the two-month standard deviation of daily growth rates on crude oil prices, the two-month standard deviation of daily growth rates in bilateral exchange rates against the US dollar (foreign currency units per US$1; the euro, Canadian dollar, Japanese yen, British pound, Swiss franc, Australian dollar, and Swedish krona), and the two-month average of EPU from Baker, Bloom and Davis (2016). The light line is the first-moment of the uncertainty shocks, constructed as the first principal component of the first-moment effects the nine shocks. For oil and currencies, the first-moments are the two-month growth rates of daily oil spot prices and exchange rates. For economic policy uncertainty, we use the growth of quarterly government expenditures as a share of gross domestic product.

Table A.3. Top 30 Journals in Matched Pitchbook Sample from ProQuest

Title	Publisher	Publisher Place	Publisher Country	VC News Sample	Startup Sample
News Bites US - NASDAQ	News Bites Pty Ltd	Melbourne	Australia	1,864,638	504,350
Company Data Report	News Bites Pty Ltd	Melbourne	Australia	3,083,431	227,573
Dow Jones Institutional News	Dow Jones & Company Inc.	New York	United States	1,095,270	183,489
News Bites US - NYSE	News Bites Pty Ltd	Melbourne	Australia	1,658,579	156,218
Newstex Finance & Accounting Blogs	Newstex	Chatham	United States	923,161	150,213
PR Newswire	PR Newswire Association LLC	New York	United States	625,507	120,162
Business Wire	Business Wire	New York	United States	441,141	94,280
News Bites - Private Companies	News Bites Pty Ltd	Melbourne	Australia	446,757	60,357
Quarterly Research Reports	News Bites Pty Ltd	Melbourne	Australia	600,351	44,567
Newstex Global Business Blogs	Newstex	Chatham	United States	275,237	42,917
Private Company Research Reports	News Bites Pty Ltd	Melbourne	Australia	401,081	42,818
TCA Regional News	Tribune Content Agency LLC	Chicago	United States	297,942	39,562
CE Noticias Financieras	ContentEngine LLC	Miami	United States	314,357	36,275
NASDAQ OMX's News Release Distribution Channel	NASDAQ OMX Corporate Solutions, Inc.	New York	United States	169,201	33,963
Targeted News Service	Targeted News Service	Washington, D.C.	United States	212,343	23,893
New York Times (Online)	New York Times Company	New York	United States	94,264	21,245
Wall Street Journal (Online)	Dow Jones & Company Inc.	New York, N.Y.	United States	71,007	20,216
M2 Presswire	Normans Media Ltd	Coventry	United Kingdom	146,093	19,867
Wall Street Journal	Dow Jones & Company Inc.	New York, N.Y.	United States	92,632	16,096
Canada NewsWire	PR Newswire Association LLC	Ottawa	United States	123,866	13,502
MENA Report	Disco Digital Media, Inc.	Camden	United States	157,776	11,383
Benzinga Newswires	Accretive Capital LLC d/b/a Benzinga	Southfield	United States	32,442	10,628
New York Times	New York Times Company	New York, N.Y.	United States	75,304	10,430
TechCrunch	AOL Inc.	New York	United States	24,065	10,027
University Wire	Uloop, Inc.	Carlsbad	United States	60,976	9,955
Financial Services Monitor Worldwide	Disco Digital Media, Inc.	Amman	United States	59,741	9,873
Newstex Trade & Industry Blogs	Newstex	Chatham	United States	33,569	9,193
The Economic Times	Bennett, Coleman & Company Limited	New Delhi	India	67,455	9,148
peHUB	PEI Media Group	New York	United States	31,251	8,987
Business Insider	Insider, Inc.	New York	United States	19,992	8,942

Notes. This table provides the list of the top 30 journals from ProQuest in terms of their news articles that can be matched to the PitchBook startup sample. VC News Sample is the number of news articles mentioning entrepreneurship related words and Startup Sample is the number of news articles matched to the PitchBook startup sample.

Table A.4. News Mentions and Startup Activities

Panel (a): News Mentions and Startup Financing

	(1)	(2)	(3)	(4)	(5)
		ln(VC Deal Amount)			
$Y_{f,t}$ =	1(VC Deal)	Current	Past 4Q	Cumulative	ln(Num. Investors)
1(Financing News Mention)$_{f,t}$	0.032***	0.042***	0.099***	0.271***	0.108***
	(0.001)	(0.001)	(0.003)	(0.004)	(0.002)
1(VC News Mentions)$_{f,t}$	0.181***	0.485***	0.071***	0.171***	0.121***
	(0.002)	(0.005)	(0.005)	(0.005)	(0.003)
Observations	4,723,766	4,723,766	4,723,766	4,723,766	4,723,766
R-squared	0.087	0.119	0.292	0.779	0.694
No. of Firms	147,238	147,238	147,238	147,238	147,238
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Panel (b): News Mentions and Startup Growth and Innovation Activities

	(1)	(2)	(3)	(4)	(5)
$Y_{f,t}$ =	ln(Age)	ln(Employment)	ln(Trademark)	ln(Patent)	ln(CW Patent)
1(Financing News Mention)$_{f,t}$	0.040***	0.276***	0.011***	0.014***	0.018***
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
1(VC News Mentions)$_{f,t}$	0.042***	0.096***	0.011***	0.017***	0.026***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)
Observations	4,723,766	3,580,570	4,723,766	4,723,766	4,723,766
R-squared	0.808	0.845	0.105	0.423	0.387
No. of Firms	147,238	116,040	147,238	147,238	147,238
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Panel (a): News Mentions and Startup Exit

	(1)	(2)	(3)
$Y_{f,t}$ =	IPO	M&A	Bankruptcy
1(Financing News Mention)$_{f,t}$	-0.000*	0.012***	-0.002***
	(0.000)	(0.000)	(0.000)
1(VC News Mentions)$_{f,t}$	0.008***	0.005***	0.002***
	(0.000)	(0.001)	(0.000)
Observations	4,723,766	4,723,766	4,723,766
R-squared	0.032	0.055	0.062
No. of Firms	147,238	147,238	147,238
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes. This table presents the patterns of selection in news mentions. We compare a set of observable characteristics among the startup-quarter-level observations that have venture capital-related news mentions and those that do not have any news mentions. Furthermore, we also compare the set of characteristics when the news mentions are related to the future funding availability for startups. We include characteristics related to startup financing in Panel (a), growth measures in Panel (b), and exit outcomes in Panel (c). The model includes startup fixed effects and date fixed effects in all columns. The sample includes a startup-quarter panel with all the VC-backed startups in the Pitchbook sample starting from their founding year to the exit quarter or their twentieth year of operation. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.5. Placebo Test of Uncertainty Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Y_{f,t+4}$ =	ln(Patent)						
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Uncertainty Shocks$_{f,t}$	-0.485***				-0.454***	-0.476***	-0.513***
	(0.140)				(0.155)	(0.141)	(0.137)
First Moment$_{f,t}$	-0.017				-0.015	-0.016	0.010
	(0.125)				(0.130)	(0.128)	(0.125)
Uncertainty Shocks (2M Before)$_{f,t-1}$		-0.212			0.048		
		(0.140)			(0.146)		
First Moment (2M Before)$_{f,t-1}$		-0.294**			-0.212*		
		(0.120)			(0.125)		
Uncertainty Shocks (1Q Before)$_{f,t-1}$			-0.196			0.016	
			(0.138)			(0.136)	
First Moment (1Q Before)$_{f,t-1}$			-0.151			-0.086	
			(0.123)			(0.125)	
First Moment (2Q Before)$_{f,t-2}$				0.024			0.140
				(0.137)			(0.134)
First Moment (2Q Before)$_{f,t-2}$				-0.134			-0.081
				(0.120)			(0.120)
Observations	53,804	53,804	53,804	53,804	53,804	53,804	53,804
No. of Firms	11,981	11,981	11,981	11,981	11,981	11,981	11,981
R-squared	0.838	0.838	0.838	0.838	0.838	0.838	0.838
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table presents a placebo test to assess the validity of the instrumental variable exclusion restriction. The outcome variables include the log number of patents (ln(Patent)). Uncertainty Shocks$_{f,t}$ is the first principal component of the nine aggregate price uncertainty shocks, and First Moment$_{f,t}$ is the first principal component of the corresponding first-moment returns, as defined in Section 4.1. Columns (2)-(4) include its lagged values measured two months, one quarter, and two quarters prior to the date of financing risk, respectively. Columns (5)-(7) include both the contemporaneous uncertainty shock and its lagged values measured two months, one quarter, and two quarters prior to the date of financing risk, respectively. We divide the uncertainty shocks and its first-moment returns by 100 for readability. Controls include the current and lagged values of the outcome variable (up to four quarters), $Y_{f,t}$ and $Y_{f,t-4,t-1}$, the log VC funding in the current and prior four quarters, cumulative VC funding, startup age, number of employees, and both total and financing-related news mentions. All variables are defined and described in Table 2. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using OLS. The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.6. Financing Risk and Startup Activity Across Startup VC Stage

Panel (a): For Early-Stage Startups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.889**	-0.848	-2.405***	-0.714	0.018	-0.056	0.059
	(0.417)	(0.628)	(0.582)	(0.466)	(0.091)	(0.120)	(0.042)
$Y_{f,t}$	0.002	-0.045	0.495***	-0.240***			
	(0.051)	(0.032)	(0.020)	(0.020)			
$Y_{f,t-1,t-4}$	-0.036	-0.113***		-0.287***			
	(0.041)	(0.028)		(0.015)			
First-Stage F-Statistic	28.02	27.93	27.62	27.91	27.86	27.86	27.86
Observations	25,187	25,187	25,107	25,187	25,187	25,187	25,187
No. of Firms	7,496	7,496	7,467	7,496	7,496	7,496	7,496
R-squared	-0.183	-0.055	-0.794	0.035	0.011	-0.004	-0.039
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Panel (b): For Late-Stage Startups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.748**	-1.100**	-1.627***	-0.776**	-0.371***	-0.158	0.065*
	(0.312)	(0.452)	(0.269)	(0.325)	(0.109)	(0.099)	(0.035)
$Y_{f,t}$	0.150***	0.075***	0.758***	-0.099***			
	(0.018)	(0.016)	(0.015)	(0.020)			
$Y_{f,t-1,t-4}$	0.123***	0.075***		-0.136***			
	(0.018)	(0.017)		(0.013)			
First-Stage F-Statistic	72.40	72.18	72.16	71.94	72.58	72.58	72.58
Observations	24,836	24,836	24,786	24,836	24,836	24,836	24,836
No. of Firms	5,334	5,334	5,319	5,334	5,334	5,334	5,334
R-squared	0.009	-0.032	0.111	-0.035	-0.081	-0.026	-0.029
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, by separately considering early-stage startups in Panel (a) and late-stage startups in Panel (b). Early-stage startups are defined as startups that have not received VC financing classified as late-stage VC, and late-stage startups are defined as startups that have received at least once VC financing classified as late-stage VC. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.7. Financing Risk and Startup Activity Across Startup Size

Panel (a): For Small-Size Startup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.493	-0.145	-2.683***	-0.944*	-0.257*	0.128	-0.001
	(0.610)	(0.967)	(0.817)	(0.573)	(0.132)	(0.183)	(0.068)
$Y_{f,t}$	-0.037	-0.043*	0.512***	-0.271***			
	(0.025)	(0.023)	(0.022)	(0.025)			
$Y_{f,t-1,t-4}$	-0.070***	-0.095***		-0.239***			
	(0.022)	(0.022)		(0.018)			
First-Stage F-Statistic	16.42	16.31	15.94	16.41	16.36	16.36	16.36
Observations	19,971	19,971	19,833	19,971	19,971	19,971	19,971
No. of Firms	6,224	6,224	6,181	6,224	6,224	6,224	6,224
R-squared	-0.032	0.015	-0.978	-0.080	-0.127	-0.018	0.002
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Panel (b): For Large-Size Startup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.757***	-1.094***	-1.478***	-0.728**	-0.180**	-0.195**	0.066**
	(0.265)	(0.387)	(0.222)	(0.284)	(0.081)	(0.082)	(0.028)
$Y_{f,t}$	0.196***	0.116***	0.774***	-0.068***			
	(0.019)	(0.015)	(0.012)	(0.016)			
$Y_{f,t-1,t-4}$	0.151***	0.087***		-0.146***			
	(0.018)	(0.017)		(0.012)			
First-Stage F-Statistic	96.56	96.47	96.41	96.13	96.41	96.41	96.41
Observations	30,541	30,541	30,541	30,541	30,541	30,541	30,541
No. of Firms	6,011	6,011	6,011	6,011	6,011	6,011	6,011
R-squared	0.040	-0.022	0.223	-0.019	-0.012	-0.052	-0.037
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, by separately considering small-size startups in Panel (a) and large-size startups in Panel (b). Small-size and large-size startups are cut by the median of the number of employees each quarter. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.8. Financing Risk and Startup Activity Across Startup Age

Panel (a): For Startup with Age <= 5Y

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-1.022*	-1.776*	-3.148***	-0.980*	-0.220**	-0.030	0.038
	(0.597)	(0.935)	(0.727)	(0.585)	(0.107)	(0.127)	(0.058)
$Y_{f,t}$	-0.017	-0.059***	0.458***	-0.221***			
	(0.022)	(0.018)	(0.026)	(0.020)			
$Y_{f,t-1,t-4}$	-0.090***	-0.153***		-0.269***			
	(0.019)	(0.016)		(0.015)			
First-Stage F-Statistic	26.96	26.98	26.66	27	27.04	27.04	27.04
Observations	24,432	24,432	24,367	24,432	24,432	24,432	24,432
No. of Firms	7,138	7,138	7,115	7,138	7,138	7,138	7,138
R-squared	-0.158	-0.197	-1.297	-0.022	-0.089	0.002	-0.007
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Panel (b): For Startup with Age > 5Y

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-1.033***	-1.298***	-1.488***	-1.008***	-0.293***	-0.149	0.074**
	(0.276)	(0.408)	(0.243)	(0.311)	(0.090)	(0.095)	(0.030)
$Y_{f,t}$	0.126***	0.064***	0.744***	-0.107***			
	(0.020)	(0.017)	(0.014)	(0.020)			
$Y_{f,t-1,t-4}$	0.095***	0.064***		-0.152***			
	(0.020)	(0.018)		(0.014)			
First-Stage F-Statistic	68.27	67.83	68.57	67.90	68.35	68.35	68.35
Observations	25,351	25,351	25,293	25,351	25,351	25,351	25,351
No. of Firms	5,784	5,784	5,767	5,784	5,784	5,784	5,784
R-squared	-0.120	-0.097	0.088	-0.093	-0.051	-0.027	-0.049
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, by separately considering young startups in Panel (a) and old startups in Panel (b). Young startups are defined as startups with age less than or equal to 5 years, and old startups are defined as startups with age greater than 5 years. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.9. Financing Risk and Startup Activity, With Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.542***	-0.705***	-1.311***	-0.424**	-0.134***	-0.018	0.050***
	(0.153)	(0.222)	(0.134)	(0.167)	(0.039)	(0.042)	(0.019)
$Y_{f,t}$	0.246***	0.162***	0.746***	-0.016			
	(0.013)	(0.010)	(0.007)	(0.011)			
$Y_{f,t-1,t-4}$	0.179***	0.116***		-0.095***			
	(0.011)	(0.010)		(0.008)			
First-Stage F-Statistic	244.7	244.2	241.4	243.4	244.6	244.6	244.6
Observations	87,535	87,535	87,287	87,535	87,535	87,535	87,535
No. of Firms	15,722	15,722	15,663	15,722	15,722	15,722	15,722
R-squared	0.077	0.023	0.361	-0.005	-0.014	0.002	-0.026
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, using the full sample of startup-quarter observations. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample includes all U.S. VC-backed startups with available financing risk measures. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.10. Financing Risk and Startup Activity, With Various Post-Financing Periods

Panel (a): Using Sample of Startups Who Received Financing in the Past 2 Quarters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.858**	-1.287**	-2.470***	-1.216***	-0.275***	-0.076	0.034
	(0.340)	(0.525)	(0.390)	(0.377)	(0.106)	(0.099)	(0.034)
$Y_{f,t}$	0.177***	0.097***	0.724***	-0.097***			
	(0.018)	(0.015)	(0.012)	(0.015)			
$Y_{f,t-1,t-4}$	0.156***	0.087***		-0.135***			
	(0.015)	(0.014)		(0.011)			
First-Stage F-Statistic	68.75	68.46	68.06	68.24	68.54	68.54	68.54
Observations	36,436	36,436	36,353	36,436	36,436	36,436	36,436
No. of Firms	9,752	9,752	9,724	9,752	9,752	9,752	9,752
R-squared	0.014	-0.041	-0.054	-0.114	-0.059	-0.003	-0.008
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post (2Q)	Post (2Q)	Post (2Q)	Post (2Q)	Post (2Q)	Post (2Q)	Post (2Q)

Panel (b): Using Sample of Startups Who Received Financing in the Past 4 Quarters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.791***	-0.996**	-2.093***	-1.031***	-0.223***	-0.054	0.044
	(0.262)	(0.394)	(0.277)	(0.280)	(0.074)	(0.077)	(0.028)
$Y_{f,t}$	0.180***	0.106***	0.716***	-0.089***			
	(0.017)	(0.013)	(0.010)	(0.014)			
$Y_{f,t-1,t-4}$	0.146***	0.079***		-0.138***			
	(0.015)	(0.013)		(0.010)			
First-Stage F-Statistic	107.3	107	106.4	106.9	107.2	107.2	107.2
Observations	47,237	47,237	47,124	47,237	47,237	47,237	47,237
No. of Firms	11,209	11,209	11,174	11,209	11,209	11,209	11,209
R-squared	0.010	-0.017	0.027	-0.087	-0.040	-0.000	-0.013
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post (4Q)	Post (4Q)	Post (4Q)	Post (4Q)	Post (4Q)	Post (4Q)	Post (4Q)

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, using the sample of startups who received financing in the past 2 quarters in Panel (a) and 4 quarters in Panel (b). The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample includes all U.S. VC-backed startups with available financing risk measures. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.11. Financing Risk and Startup Activity, With Inverse Probability Weighting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.690**	-0.750*	-1.868***	-0.869***	-0.226**	-0.141*	0.061*
	(0.274)	(0.386)	(0.259)	(0.303)	(0.092)	(0.081)	(0.035)
$Y_{f,t}$	0.206***	0.125***	0.703***	-0.074***			
	(0.022)	(0.017)	(0.012)	(0.019)			
$Y_{f,t-1,t-4}$	0.157***	0.092***		-0.147***			
	(0.020)	(0.017)		(0.014)			
First-Stage F-Statistic	110.4	109.8	109.4	109.1	109.7	109.7	109.7
Observations	53,804	53,804	53,665	53,804	53,804	53,804	53,804
No. of Firms	11,981	11,981	11,939	11,981	11,981	11,981	11,981
R-squared	0.061	0.022	0.064	-0.040	-0.023	-0.026	-0.015
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, using inverse probability weighting to account for the selection of startups into news mentions. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). We reweight based on the probability of financing news mentions, where inverse probabilities are based on predicted values from the Probit models using the full set of controls in Equation (15), as well as four additional controls: the number of VC news and financing news in the past four quarters and the cumulative number of VC and financing news. The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.12. Financing Risk and Startup Activity, Controlling for Market Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-0.936***	-1.158***	-2.322***	-1.072***	-0.264***	-0.144*	0.061**
	(0.286)	(0.430)	(0.306)	(0.300)	(0.079)	(0.083)	(0.031)
Sentiment (LM)$_{f,t}$	-0.041***	-0.052***	-0.101***	-0.043***	-0.011***	-0.007*	0.002
	(0.013)	(0.020)	(0.014)	(0.014)	(0.004)	(0.004)	(0.001)
Sentiment (GHR)$_{f,t}$	-0.017***	-0.023***	-0.032***	-0.023***	-0.005***	-0.004**	0.001
	(0.005)	(0.008)	(0.006)	(0.006)	(0.002)	(0.002)	(0.001)
$Y_{f,t}$	0.193***	0.117***	0.720***	-0.080***			
	(0.017)	(0.013)	(0.010)	(0.014)			
$Y_{f,t-1,t-4}$	0.138***	0.074***		-0.141***			
	(0.014)	(0.013)		(0.010)			
First-Stage F-Statistic	99.20	99.02	98.57	98.68	99.15	99.15	99.15
Observations	53,804	53,804	53,665	53,804	53,804	53,804	53,804
No. of Firms	11,981	11,981	11,939	11,981	11,981	11,981	11,981
R-squared	-0.018	-0.035	-0.079	-0.090	-0.059	-0.026	-0.026
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, after adding two measures of sentiment as additional control variables. Sentiment (LM)$_{f,t}$ and Sentiment (GHR)$_{f,t}$ are two measures of sentiments from Loughran and McDonald (2011) and Garcia, Hu and Rohrer (2023), respectively. This table examines the relation between financing risk and startup entrepreneurial activities, using inverse probability weighting to account for the selection of startups into news mentions. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.13. Financing Risk and Startup Activity, Controlling for Expectations of Startup Quality Concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Innovation		Growth		Exit		
$Y_{f,t+4}$ =	ln(Patent)	ln(CW Patent)	ln(Employment)	ln(Trademark)	1(IPO)	1(M&A)	1(Bankruptcy)
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Financing Risk$_{f,t}$	-1.669***	-2.051**	-4.107***	-1.919***	-0.477***	-0.265*	0.106*
	(0.537)	(0.797)	(0.673)	(0.567)	(0.148)	(0.152)	(0.057)
Quality Risk$_{f,t}$	0.746***	0.915**	1.808***	0.852***	0.215***	0.125*	-0.044*
	(0.244)	(0.362)	(0.306)	(0.257)	(0.067)	(0.069)	(0.026)
$Y_{f,t}$	0.192***	0.115***	0.712***	-0.079***			
	(0.017)	(0.013)	(0.012)	(0.014)			
$Y_{f,t-1,t-4}$	0.138***	0.073***		-0.143***			
	(0.014)	(0.013)		(0.010)			
First-Stage F-Statistic	52.83	52.67	51.79	52.56	52.84	52.84	52.84
Observations	53,804	53,804	53,665	53,804	53,804	53,804	53,804
No. of Firms	11,981	11,981	11,939	11,981	11,981	11,981	11,981
R-squared	-0.135	-0.116	-0.776	-0.229	-0.147	-0.060	-0.059
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Industry-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Moment Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Post	Post	Post	Post	Post	Post	Post

Notes. This table examines the relation between financing risk and startup entrepreneurial activities, after adding startup quality risk as additional control variable. Quality Risk$_{f,t}$ captures the startup's quality, operation and performance that could influence future funding availability, as defined in Section 3.2.3. The empirical design follows that in Table 4, Table 6, and Table 7. The model includes startup fixed effects and state-industry-period fixed effects in all columns. The model is estimated using 2SLS and first-stage F-statistics are reported, following the specification in Equation (17). The sample contains the startup-quarter observations that received VC financing within the last six quarters. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.