When Lenders Meet Venture Capitalists: Relationships in Venture Debt*

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Abstract

We study how relationships between lenders and venture capital (VC) investors shape venture debt deals and startups' post-deal outcomes. We develop a model that highlights two competing mechanisms of this relationship: an information channel in which lenders benefit from VC certification and a market power channel in which lenders extract rents through bargaining power. Using a comprehensive dataset on global venture debt, we test these channels at different stages of venture debt. At entry, the relationships mitigate asymmetric information and increase the likelihood of obtaining venture debt. In the investment stage, relationship lenders reduce hard restrictions while charging higher spreads. Post-deal, relationship-backed startups are more likely to secure subsequent VC funding and successful exits by reallocating innovation toward commercially salient and safer projects. Our findings highlight that VC-lender relationships alleviate information frictions and allow rent extraction, yet ultimately facilitate value creation in high-growth ventures.

Keywords: Venture Debt, Relationships, Venture Capital, Asymmetric Information
JEL Codes: G23, G24, L26, O32, D82

*This version: November 14, 2025. We thank Paul Goldsmith-Pinkham, Song Ma, Kelly Shue, Yao Zeng, and workshop participants at Yale (Finance) for their useful comments. All errors are our own.

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1. Introduction

Venture capital–backed startups are widely recognized as engines of technological progress and economic growth (Kortum and Lerner, 2000; Samila and Sorenson, 2011). Their reliance on debt financing is common in practice but has received little attention in academic research (Morse, 2024). Venture debt, a type of loan offered by banks and non-bank lenders for VC-backed, high-growth companies, has experienced tremendous growth in recent years, surpassing 30 billion USD in annual deal activity after 2020[1] and now accounting for 15% of VC investment. The prominence of specialized lenders such as Silicon Valley Bank illustrates both the scale and fragility of this market. While venture debt fills a financing gap for firms with limited collateral or cash flows, the opacity of these borrowers makes lending inherently risky (Jiang et al., 2024; Drechsler et al., 2023). Like traditional banking, relationship lending mitigates risk and information frictions (Sharpe, 1990; Rajan, 1992), playing a central role in shaping access to credit and contract terms in the venture debt market.

In this paper, we study the importance of relationships in venture debt. Unlike conventional interactions with borrowers, venture lenders form relationships with *venture capitalists*. This type of relationship is unique because the contract claims are directly against the startup, not the VC investors. However, VC investors effectively act as shadow borrowers, as they control key decisions of the startups. In this context, venture lenders use VC support as a source of validation and the primary yardstick for underwriting a loan.[2] With this in mind, we ask: How do lender-VC relationships influence venture debt decisions and post-deal startup outcomes, and through which channels do these effects arise?

We approach these questions both theoretically and empirically. Our stylized model highlights two key mechanisms of relationships. On the one hand, the *information channel* captures how venture lenders benefit from VC certification to resolve information asymmetry. On the other hand, the *market power channel* reflects how repeated interactions strengthen lenders' bargaining position over startups due to switching costs and matching frictions. Empirically, we use a comprehensive contract-level dataset on the global venture

[1] https://my.pitchbook.com/research-center/report/95bfd5df-4eae-36d6-b6d5-9caeec39909a

[2] https://www.svb.com/startup-insights/venture-debt/how-does-venture-debt-work

debt market to test these mechanisms. We document that relationships matter for venture lending and post-deal outcomes in startups. At entry, relationships with VCs expand lenders' willingness to invest in firms with high information asymmetry. In the investment stage, relationships allow lenders to provide contracts with fewer restrictions while charging a higher spread. Post-deal, relationships allow startups to secure more follow-on capital, achieve value-creating exits, and reallocate innovation to commercially salient and safer projects.

A central challenge in studying venture debt is the lack of comprehensive data. Unlike venture capital investments, venture debt transactions occur in private credit markets with limited disclosure. We address this challenge by assembling a new dataset that overcomes this limitation through several dimensions of data effort. First, we collect global venture debt market data from PitchBook, which records over 15,000 venture debt deals involving more than 11,000 startups from 1996 to 2014 across 110 countries. Second, we exploit detailed information on deal terms at the facility level, including load spread, size, maturity, and key contract attributes, which allows us to analyze the contractual design of venture debt. Third, we consolidate a rich set of private firm characteristics by linking PitchBook startups to complementary data on innovation from the USPTO, employment from Revelio Labs, and news coverage from ProQuest.

With this comprehensive data on venture debt, we construct a novel measure that captures venture lenders' past relationships with venture capital of startups. We define "relationship" as historical co-participation between the lender and any of the startup's past investors. We then provide two sets of stylized facts on the relationship between venture lenders and venture capital. First, relationships with venture capital are common among venture lenders. On average, 61% of venture debt deals have a relationship with past investors, comparable to venture capitalists. Deals with relationships increase over time and become more important in periods of uncertainty, for example, after the SVB turmoil. Relationships are increasingly salient in global markets, especially in the United States and Europe, where major activities happen. Second, we show that the reliance on the relationship is heterogeneous across lenders and industries. Relationships are more prevalent among non-bank venture lenders, who have significantly increased their market share in the recent decade. We also find that the relationship is essential in highly innovative but obscure industries. The prevalence and importance of relationships in high-information-asymmetry environments motivate us to study how relationships affect every aspect of a venture debt deal. How do relationships with VCs affect how lenders select deals? How are relationships correlated with deal terms and loan prices? Do relationship-backed startups experience future firm growth?

To guide our empirical analysis, we develop a stylized framework of relationship lending in the venture debt market, built around two distinctive features. The first is the role of venture debt for startups, where startups rely on venture debt to extend runway or to complement equity rounds to avoid costly equity or down rounds (Morse, 2024; Davis, Morse and Wang, 2020; Gonzalez-Uribe and Mann, 2024). Second, unlike classic bank relationship lending where the interaction occurs between the lender and the borrower (Sharpe, 1990; Rajan, 1992; Hellmann, Lindsey and Puri, 2008), the repeated interaction in venture debt is between the lender and the startup's venture capital investors. The VC plays a central role in certifying the borrower's quality and monitoring its progress, which we call the information channel (De Rassenfosse and Fischer, 2016; Hochberg, Serrano and Ziedonis, 2018). At the same time, repeated interactions with the same investors can also strengthen the lender's bargaining position due to switching costs and matching frictions, which we call the market power channel (Dougal et al., 2015; Demiroglu, James and Velioglu, 2022). These two forces coexist and jointly determine how relationships shape the life cycle of a venture debt deal.

The model yields a set of testable predictions. First, connected startups are more likely to obtain venture debt as relationships raise lenders' beliefs about startup quality and expand the feasible set of contracts, thereby offsetting the negative impact of asymmetric information. Second, relationships reduce the need for intensive monitoring and restrictive covenants, suggesting that relationship-backed debt contains fewer hard restrictions. Third, the effect on loan spreads is ambiguous. The information channel lowers spreads by reducing perceived risk, while the market power channel raises spreads by allowing lenders to extract rents. Finally, the same logic extends to startup outcomes. The information channel implies higher growth for connected firms by increasing the total surplus, while the market power channel predicts lower growth if lenders capture a disproportionate share of the surplus.

We present three key empirical findings guided by our theoretical framework. Our first key result is how lenders' relationships with VC correlate with a startup's likelihood to obtain venture lending. Using matched control startups in the same industry, country, and stage, we first show that the relationship offsets the negative impact of asymmetric information on lenders' selection into venture debt. Using various measures of asymmetric information sourced from patent portfolios, news coverage, and distance, we document that asymmetric information reduces the possible set of firms that can obtain venture debt. However, the relationships with VC substantially mitigate these frictions and make lenders more willing to lend. A cross-industry analysis further supports this interpretation, where in R&D-intensive industries that are highly innovative but difficult to evaluate, lenders rely more heavily on their relationship with VC. Finally, to address the concern that these results reflect selection by VCs, we demonstrate that startups with relationship-backed loans are similar to those with non-relationship-backed loans across a range of profitability and commercialization measures.

Our second key empirical finding speaks to the relationship between contract design and equilibrium prices during the investment stage. Our empirical design relies on cross-sectional variations at the deal-facility level. One potential endogeneity concern is that the selection of relationship lenders may be correlated with the deal or the startup. Thus, following the instrumental variable (IV) approach in Ivashina and Kovner (2011), we exploit variation in the concentration of VCs' prior lending relationships before the focal deal. The motivation is that a VC has less bargaining power if its lending relationships are highly concentrated among a small set of lenders. To restore power, the VC is more likely to select a non-relationship lender, leading to a negative correlation between the VCs' prior lender concentration and the relationship measure. Importantly, our instrument is constructed solely from the VCs' prior relationship structure, which is plausibly exogenous to unobserved characteristics of the current startup, deal, or lender.

Regarding deal terms, we find that lenders that have relationships with startups' past investors tend to offer more flexible contracts with fewer hard restrictions. Loans provided by lenders with relationships are, on average, 10% more likely to be unsecured and 1% less likely to be first lien. These lenders also modify the loan structure with less monitoring intensity. Having relationships makes lenders 3% less likely to issue a term loan, and 1.1% more likely to issue revolving credit. These patterns suggest that relationships substitute for intensive monitoring and collateral requirements, consistent with our information channel.

At the same time, relationship lenders charge significantly higher interest spreads. Relative to non-relationship lenders, relationship lenders can charge a 149-basis-point higher spread on their venture loans, accounting for 19% of the sample mean. The higher spread is robust across various firm- and loan-characteristics controls and fixed effects. These consistent results highlight the dominance of the market power channel in determining loan prices, allowing lenders to extract rents from startups through stronger negotiation power.

To further understand the mechanisms through which relationships enhance lenders' bargaining power, we examine how outside options and VC-startup agency conflicts affect the high spread charged on relationship-backed loans. First, we find that the effect on the spread is concentrated among deals in which the startup's VCs and the startup itself have fewer alternative lenders. This is consistent with the market power channel, where the exclusive relationship creates hold-up opportunities for lenders to extract rents from startups (Sharpe, 1990; Petersen and Rajan, 1995). Second, VC-startup agency conflicts also allow lenders to charge a higher spread because the VC is making a strategic trade-off across its broader portfolio of investments. We find that the spread charged on relationship-backed loans is significantly higher when VCs have greater influence or are more established repeat players. We measure VC influence by the number of current VC shareholders, their average age, and the number of portfolio companies.

Our last key result focuses on the consequences for startup growth and value creation. We first show that relative to non-relationship borrowers, relationship-backed startups are 2.2% more likely to raise a subsequent venture capital round and raise 11% more capital, offsetting nearly three-quarters of the equity substitution effects associated with debt financing alone. Regarding exits, relationship-backed startups are 21 basis points more likely to go public and 44 basis points more likely to be acquired, which are equivalent to 117% of the average IPO rate and 62% of the average merger-and-acquisition rate in our sample. At the same time, no evidence suggests an increase in bankruptcy risk. These patterns are consistent with the information channel in our framework, where relationships ease verification and allow young firms to secure follow-on capital and achieve value-creating exits.

We then examine how these effects are transmitted using innovation strategies. Startups with relationship-backed debt produce 10% more patents and 12% quality-weighted patents, relative to sample means, eliminating the modest declines observed for non-relationship borrowers. More importantly, the composition of innovative output shifts. These startups produce more product patents than process innovation. This is consistent with the notion that product innovation serves as observable milestones that resolve uncertainty and support external financing (Gonzalez-Uribe and Mann, 2024). The gains concentrate in projects that are less resource-intensive and easier to certify, including incremental rather than breakthrough innovations (Kelly et al., 2021) and exploitative rather than explorative innovations (Almeida, Hsu and Li, 2013). Thus, relationships do not simply expand the scale of innovative activity but redirect post-deal effort toward commercially salient and safer projects that generate earlier signals to investors and facilitate subsequent financing and exits.

Related Literature Our paper relates to several strands of literature. Our paper builds on the emerging literature that examines the role of debt financing for VC-backed firms. As emphasized in the recent survey by Morse (2024), the existence of venture lending is a puzzle, where debt would appear to be a suboptimal form of financing given the extreme uncertainty and limited cash flows of high-growth startups(Gompers and Lerner, 1996; Mann, 1999; Winton and Yerramilli, 2008; Ibrahim, 2010). One line of work has pointed out that intellectual property, especially patents, can provide meaningful collateral (Mann, 1999; De Rassenfosse and Fischer, 2016; Chava, Nanda and Xiao, 2017; Mann, 2018; Brown, Harris and Munday, 2021; Hochberg, Serrano and Ziedonis, 2018). More closely related to our study are Tykvová (2017), Davis, Morse and Wang (2020), and Gonzalez-Uribe and Mann (2024), who highlight that startups use venture debt to extend runway and argue its relationship business. Our contribution is to formalize the lender–VC relationship in a simple model of lending decisions, and to provide the first systematic empirical evidence on how these relationships shape the full life cycle of venture debt, from access and contract terms to post-deal startup outcomes.

The paper is also related to the growing literature on private credit markets. A large body of work has documented the rapid expansion of nonbank lending, often attributed to increased bank regulation (Chen, Hanson and Stein, 2017; Cortés et al., 2020; Gopal and Schnabl, 2022; Chernenko, Erel and Prilmeier, 2022; Aldasoro, Doerr and Zhou, 2023; Chernenko, Ialenti and Scharfstein, 2025) or the demand for flexibility (Buchak et al., 2018; Haque, Mayer and Wang, 2024; Haque, Mayer and Stefanescu, 2024; Davydiuk et al., 2024). Together, these forces have shifted banks' lending away from corporate borrowers and toward nonbank lenders (Jiang, 2023; Krainer, Vaghef and Wang, 2024; Acharya et al., 2025; Haque, Jang and Wang, 2025), and have important implications for macro finance (Xiao, 2020; Agarwal et al., 2022; Cucic and Gorea, 2022; Jang and Rosen, 2025; Haque, Jang and Wang, 2025; Fleckenstein et al., 2025). In terms of monitoring and covenants, direct lenders often substitute for banks by engaging in intensive monitoring and including detailed covenants (Jang, 2024; Davydiuk, Marchuk and Rosen, 2024; Block et al., 2024; Haque, Mayer and Wang, 2024; Haque, Mayer and Stefanescu, 2024). At the same time, Chernenko, Erel and Prilmeier (2022) show that nonbank borrowers are more unprofitable and riskier and, thus, their loan contracts are less likely to include financial covenants but warrants. Our contribution is to extend this literature by showing that venture debt, as a specialized and early segment of private credit, relies on relationships with VC both to certify borrower quality and to secure future capital, underscoring the central role of relationships in sustaining credit markets that operate in highly opaque environments.

This paper connects to a growing literature on contracting and financing for low-tangibility, innovative firms. Prior work highlights the role of intellectual property, especially patents, in supporting debt financing (Hellmann, Lindsey and Puri, 2008; Robb and Robinson, 2014; Lim, Macias and Moeller, 2020; Mann, 2018), and examines how contractual terms shape valuation and incentives (KAPLAN and STROMBERG, 2003; Kaplan and Strömberg, 2004; Hsu, 2004; Cumming, 2008; Bengtsson and Sensoy, 2011; Gornall and Strebulaev, 2020; Ewens, Gorbenko and Korteweg, 2022). Closely related to us is Hellmann, Lindsey and Puri (2008), who studies the relationship between lenders and innovative firms. Our paper instead documents a different mechanism through which high-growth startups access financial markets, where relationships between lenders and VCs substitute for traditional collateral and contractual protections.

This paper draws inspiration from the substantial literature on bank lending relationship (Sharpe, 1990; Rajan, 1992; Bharath et al., 2007; Beck et al., 2018; Elyasiani and Goldberg, 2004). Prior work shows that close lender–borrower ties can ease credit constraints, allowing firms to obtain more financing or better terms during recessions (Bolton et al., 2016; Beck et al., 2018; Karolyi, 2018; Banerjee, Gambacorta and Sette, 2021). These benefits arise because repeated interactions reduce costs from ex-ante due diligence and ex-post costly state verification (Williamson, 1987; Garleanu and Zwiebel, 2009; Bharath et al., 2011; Prilmeier, 2017). At the same time, relationship also generates path dependence in pricing, enabling lenders to extract rents (Petersen and Rajan, 1995; Schenone, 2010; Ioannidou and Ongena, 2010; Dougal et al., 2015; Demiroglu, James and Velioglu, 2022; Beraldi, 2025). We extend this literature by showing that, in the context of venture debt, the key relationship is not between the lender and the borrowing firm in venture debt, but between the lender and the VC (i.e., its equity holder). A closely related study is Ivashina and Kovner (2011), who examine relationships between lenders and private equity firms in the leveraged buyout market. They find that bank relationships with private equity sponsors are associated with lower loan spreads, interpreting this as evidence that repeated interactions help reduce inefficiencies from information asymmetry. By contrast, our paper focuses on the venture debt market and finds that lender-VC relationships are associated with higher spreads. Moreover, we provide evidence consistent with both channels of relationship lending, information benefits and market power.

2. Venture Debt in Global Market

2.1. Institutional Background

Venture debt is a specialized type of debt financing provided to VC-backed, growth-stage companies. It complements equity financing rather than replaces it by providing working capital and extending the runway between equity rounds or alongside them. Typical structures include bridge loans that carry a company to the following equity round, venture leverage that layers with an equity round, or patent loans collateralized by intellectual property (Morse, 2024).

Unlike traditional bank lending that relies on positive cash flows or hard assets as collateral, underwriting in this market is tied to expectations about future equity rounds and liquidity events (e.g., IPOs or acquisitions). Contracts often make these events explicit through covenants and trigger events. Venture debt is typically structured as short maturities, staged draws, and milestone-contingent funding. The design reflects that firm value primarily stems from growth opportunities and intangible assets rather than current earnings.

The venture capital investor is central to the functioning of this market because it mitigates asymmetric information problems (De Rassenfosse and Fischer, 2016; Hochberg, Serrano and Ziedonis, 2018). They have performed due diligence and capital investment, acting as certification for lenders. Meanwhile, they actively monitor the startup's progress, reducing the moral hazard problem. Lenders can rely on the VC's oversight, effectively lowering their monitoring costs. In addition, VCs provide an implicit guarantee. Since they have strong incentives to protect their equity investment, they are often willing to supply bridge financing or lead new rounds of capital when portfolio firms face distress, thereby indirectly protecting lenders' claims.

This deep involvement of the VC means that the lender's primary underwriting decision depends not only on the startup's fundamentals but also on the reputation and commitment of its VC sponsor. Over time, repeated interactions between a concentrated set of VCs and lenders produce persistent relationships. These relationships are central to understanding the dynamics of the venture debt market and form the focus of this paper.

2.2. Data and Measurement

2.2.1. Data and Sample Construction

The primary data source on the global venture debt market for this paper is PitchBook, a leading database for VC-backed startups. PitchBook aggregates information from regulatory filings (e.g., SEC Form D), direct contacts with funds and portfolio firms, and news sources. It has been used by the National Venture Capital Association, the U.S. National Science Board, and others. We focus on the universe of startups in PitchBook that received at least one round of venture capital financing, with deals categorized as all VC stages,[3] and marked as "Completed". From PitchBook, we extract firm-level information, including legal name, founding year, location, industry, and LinkedIn URL. PitchBook also records outcome events, including bankruptcy, mergers and acquisitions, and IPOs. For a subset of deals, PitchBook reports contemporaneous financials at the time of the transaction, including total debt, revenue, EBITDA, and net income.

While PitchBook does not directly label a deal as venture debt, we identify venture debt deals based on their type and startup status. We classify a deal as venture debt of a VC-backed company if (1) the deal is labeled as a debt financing or has at least one lender, and (2) the deal date occurs strictly before the first private equity (PE), IPO, or M&A event, or before the final VC financing event. The intuition is that venture debt is typically issued during the VC stage, before exit or transition to PE ownership. This gives us a sample of 15,451 venture debt deals over 1996-2024 from 11,249 VC-backed startups of 41 industry groups across 110 countries.[4]

A venture debt deal is typically organized into one or more facilities, each representing a loan provided by a distinct lender group and potentially differing in size, pricing, and contractual terms. In our data, 83% (= 12,883/15,451) of venture debt deals have non-missing facility records. For each facility, we observe lender names, loan spread, loan size, maturity, and key contract attributes including facility type (i.e., term loan vs. revolving credit), seniority, security (i.e., secured, first lien, etc.), covenant-lite indicators, and

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

[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).

convertibility.

We supplement startup data with worker-level profiles from Revelio Labs, which compile employment histories from LinkedIn. This dataset offers broad coverage in the U.S., especially for private firms (Babina et al., 2024). We use these data to construct firm-level employment aggregates and composition measures.

To obtain the innovation profile of a startup, we obtain patent data from the United States Patent and Trademark Office (USPTO), covering eight million patents granted by the USPTO from 1976 to 2024.[5] For each patent, we observe application and grant dates, Cooperative Patent Classification (CPC) technology classes, and assignee name and location. Following Kogan et al. (2021), patent quality is measured by citation-weighted counts, defined as the number of citations received by the patent, scaled by the average number of citations from its own vintage and technology class. We also compute various patent measures to capture the type of patent: whether it serves for product or process innovation (Bena and Simintzi, 2023), an explorative measure to proxy the intensity with which a firm innovates based on knowledge that is new to the firm (Manso, 2011; Almeida, Hsu and Li, 2013; Custódio, Ferreira and Matos, 2019), a breakthrough measure to proxy the extent to which a patent is a breakthrough patent (Kelly et al., 2021),[6] and a redeployability measure to proxy the extent to which the value of a patent is redeployable by other firms (Ma, Tong and Wang, 2022).

We use the ProQuest news corpus data from Chen (2024) to capture press visibility. The news data from ProQuest used in this paper contains three complementary news databases, including ProQuest ABI/Inform Collection, U.S. Newsstream Database, and European Newsstream Database. Together, they include the news and popular press articles and journal articles on business subjects in the U.S. and European countries from 1980 to 2023.

Following Chen (2024), we link the supplementary datasets to PitchBook using a two-step procedure. We first use fuzzy matching based on standardized company names, locations, and basic identifiers. We then manually verify high-scoring conflicts and large firms.

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

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

When available, LinkedIn URLs from PitchBook anchor the match to Revelio Labs.

2.2.2. Measuring Venture Debt Relationship

We measure whether a venture debt deal is supported by preexisting relationships between its lenders and the startup's prior investors. A "relationship" here is a historical co-participation between a current lender and any of the startup's past investors before the focal deal date. Co-participation means that the lender and the investor have previously financed the same other company, though not necessarily in the same round or on the same date. If the focal deal is the startup's first recorded financing event, the relationship measures are set to missing because no information can reveal ties.

We construct two measures of the relationship between the lenders and the startup's past investors. First, I(Relationship) is a dummy indicator that equals one if the current lender has co-participated with at least one of the startup's past investors, and zero otherwise. Second, Share of Relation Investors captures the breadth of relationships, defined as the share of past investors that have previously co-participated with the current lender. All histories used to determine relationships are dated strictly before the focal deal to avoid look-ahead.

We first compute the relationship at the deal-facility-lender level, as a lender may appear on multiple facilities within the same deal. Then we aggregate upward at the facility level by taking the maximum of the relationship measures across lenders on that facility. Similarly, we aggregate upward at the deal level by taking the maximum of the relationship measures across facilities within the deal. This aggregation reflects the idea that the presence of any well-connected lender can anchor a relationship for the facility or deal.

2.2.3. Summary Statistics

We first present the aggregated venture debt activity, covering 15,451 deals between 1996 and 2014 in our sample. Panel (a) of Figure 1 plots the number of venture debt deals by quarter (left axis) and the aggregate debt amount in million dollars (right axis). The market was relatively small in the late 1990s and early 2000s, averaging fewer than 50 deals per quarter, with a brief peak in dollar amount around 2000. Venture debt activity began to grow steadily after the mid-2000s and accelerated sharply around 2010, reaching more than 200 deals per quarter at its peak. The aggregate debt amount followed a similar pattern, rising gradually in the early years before surging to more than 15 billion dollars per quarter after 2020. Overall, the figure highlights the rapid expansion of venture debt over the past two decades, both in terms of deal count and dollar volume.

[Insert Figure 1 Here.]

Table 1 Panel (a) presents the summary statistics of the venture debt deal characteristics. On average, 61% of the deals have at least one relationship with startups' prior investors, with a mean share of relationship investors of 40%. Venture debt typically arrives around the fourth financing round. Average deal size is about 40 million dollars, and 27% of deals are flagged as levered financing. Deals are lean on participants and structure, with, on average, one lender and a little over one facility per deal.

[Insert Table 1 Here.]

We also report the contract terms at the facility level in Panel (b) of Table 1. On average, the facility has a spread of 763 basis points, a facility amount of 41 million dollars, and a maturity of five years. Term loans dominate (86%) the venture debt market, while revolving credits account for 8% of the facilities. Senior (19%) and secured (23%) facilities are present but not common in the market. Cov-lite facilities and convertibles account for 0.3% and 1.8% of the facilities, respectively.

Panel (c) of Table 1 describes the borrowers at the time of the deal. Startups are small and still scaling, with 156 employees and 26 quarters of age on average. Cumulative external financing averages 113 million dollars, and total debt averages 37 million. Average revenue per employee is 2.75 million dollars, while profitability remains negative on average, with average EBITDA per employee of -0.21 million dollars and average net income per employee of -0.32 million dollars. Geography is not primarily local, with 11% of the startups located in the same city as the lender, and the average distance to the lender is 2,086 kilometers.

2.2.4. Matched Sample

Our empirical analysis of the ex-ante decision and ex-post startup performance relies on a matched sample of treated startups (i.e., those who received venture debt in a given quarter) and their counterparts. Our causal interpretation depends on a carefully chosen control group of startups and an assumption of "ignorability". Following Herkenhoff et al. (2025) and Garfinkel et al. (2025), we implement the Coarsened Exact Matching (CEM) estimator of Iacus, King and Porro (2012) on six key startup characteristics. CEM estimators prioritize sample balance, hence the best chance of finding companies comparable on unobservables, at the expense of sample size.

We build the control group of startups based on the six key startup characteristics in ex ante quarters before the focal venture debt deal. We first enforce exact matches on three dimensions where the treated and control startups are in the same country, in the same 4-digit industry group, and in the same financing stage.[7] We then apply CEM using coarse bins for three additional characteristics, including (1) startup age bins: 0-8 quarters, 8-20, 20-40, 40-80, and 80 or more quarters, (2) cumulative financing amount bins: 0 million dollars, 0-1, 1-3, 3-10, 10-25, 25-60, and 60 or more million dollars, (3) employment bins: 1-9, 10-49, 50-249, 250-499, 500-999, 1000-4999, and 5000 or more employees.

Within each matched stratum, we rank candidate controls by absolute differences in age, cumulative financing, and employment. We treat the complete matched set as the lender's consideration set for the ex-ante decision analysis in Section 4. For the ex-post startup performance analysis in Section 6, we use the closest ten matches as the control group for each treated startup.

This design yields control groups that are highly comparable to venture debt startups along key pre-treatment dimensions. One of the shortcomings is that a small sample of treated startups is dropped during the matching procedure, as the tradeoff is necessary to directly compare treated and control workers and mitigate sample selection issues.

[7]We categorize the financing stage based on the deal type category provided by PitchBook. We categorize into (1) angel/seed stage (including "Product Crowdfunding", "Equity Crowdfunding", "Accelerator/Incubator", "Angel (individual)", and "Seed Round"), (2) early VC (including "Early Stage VC"), (3) late VC (including "Later Stage VC"), and (4) PE (including "PE Growth/Expansion", "PIPE", "Buyout/LBO", "Investor Buyout by Management", and "GP Stakes"). If there is no financing event in that year-quarter, we categorize based on the latest available financing event.

Appendix Table A.2 reports balance tests. The first three rows cover the matched characteristics, including age, cumulative financing, and employment. The subsequent rows consider additional variables such as financing and innovation activities. Overall, treated and control startups are well balanced on the targeted covariates.

2.3. Stylized Facts

In this section, we present two sets of stylized facts about venture debt and its relationship with the venture capitalist. In the first fact, we document that venture debt (VD) relationships are common from three perspectives. First, venture debt relationships with startups' past investors are comparable to venture capital relationships. Second, venture debt relationships stay prevalent over time and gradually increase to around 70% after COVID-19. Third, they are common globally, especially in countries where most VD activities occur. In the second fact, we show that VD's reliance on relationships is heterogeneous across lender types and industries. Major providers of VD rely on relationships, especially private lenders who have grown their market share in the recent decade. The reliance on relationships varies between industries, higher for industries with high R&D intensity and more obscure. The maximum percentage of deals with relationships is 78% and the minimum is 37%.

Fact 1: VD relationship is common We present three evidence that the relationship is prevalent in venture debt deals. First, we compare the percentage of venture debt deals with at least one lender with prior VC ties, with the percentage of venture capital deals with at least one investor with prior VC ties. We show that 61% of venture debt deals rely on relationships and 66% of venture capital deals do. Venture debt deals depend on previous relationships with the investors of the firm, to the same extent as venture capitalists, which are known to rely on relationships for deal selection (Hochberg, Ljungqvist and Lu, 2007) and barrier to entry against outside investors (Hochberg, Ljungqvist and Lu, 2010).

Second, in Panel (b) of Figure 1, we plot the percentage of VD deals with a relationship and the average share of previous investors with relationships over deals in each quarter. We see that the relationship is prevalent and relatively stable over time, even when the amount of venture debt deals increases significantly after 2010. Since the 2000s, around 50% to 60% of venture debt deals have at least one lender with a relationship, and the average share of investors with a relationship with at least one lender ranges from 30% to 40%. The reliance on relationships has become even more pronounced in recent years, rising to around 70% after COVID-19. This is a period of heightened uncertainty marked by the collapse of Silicon Valley Bank and the rapid growth of private lenders such as credit funds and BDCs. This pattern suggests that when venture lenders' liquidity concerns increase, they lean more heavily on existing ties for screening and contracting.

Third, we demonstrate that reliance on relationships is common in VD deals globally, especially in countries where most VD activities occur. In Panel (a) of Figure 2, we plot the venture debt amount in the top 20 countries with venture debt activities. The United States is where most VD deals happen, with a total debt amount of 262 trillion USD across years, but we also have substantial VD deals in Europe and Asia. The United Kingdom and European Union have more than 50 trillion USD in market size, and China and India have around 30 trillion USD. We show in Panel (b) of Figure 2 that relationships are common among VD deals in these top 20 countries with vibrant venture debt activities. 60% of deals in the United States have a relationship, 67% in Canada. The European market relies similarly on relationships: the European Union countries have 62% deals with relationships, Switzerland 76%, and the United Kingdom 51%. For the top 20 countries in Asia, the reliance on relationships is, on average, more common. China has 57% of relationship-backed deals, India has 69%, Singapore has 63%, and Japan has 81% of the deals. In all countries where most of the global VD deals take place, on average, more than 60% of deals have a lender with prior VC ties, suggesting that reliance on relationships is an interesting global phenomenon in a growing VD market globally.

[Insert Figure 2 Here.]

Fact 2: VD relationship is heterogeneous We present a couple of facts on the heterogeneity of reliance on relationships in different lender types and industries in VD deals.

First, nonbank lenders who rely on more relationships have an increasing presence in the VD market. In Figure 3, we plot the stacked share of venture debt deals by debt amount, of major lender types over time. Historically, specialized commercial banks (e.g., Silicon Valley Bank) dominated supply, but their role declined after the early 2000s. In their place, nonbank lenders, including venture debt funds affiliated with VC and PE and specialty finance providers such as BDCs and private credit funds, have expanded rapidly. In 2000-2020, private lenders accounted for around 40% of the venture debt market, and around 50% in the years after 2020.[8] We list the top 50 venture debt lenders in Appendix Table A.1 to give examples of the largest players by type in this field.

In panel (b) of Figure 3, we plot the reliance on relationships in different lender types. We compute the percentage of lender-debt pairs with a relationship for each lender type. We see that all major lender types depend on a relationship. 45% of deals funded by a commercial bank have a relationship, and 60% of deals funded by an investment bank have a relationship. Those were the dominant lenders in the early days. Private lenders, on average, have a higher reliance on relationships, with venture capital and BDC around 70%, private equity and private credit 50%. This implies that the recent surge of private credit has therefore amplified the role of relationships in venture debt markets.

[Insert Figure 3 Here.]

Second, we show that reliance on relationships is common in all industries, but is much more prevalent in industries characterized by high R&D intensity. Table 2 lists the industries with the highest and lowest percentage of relationship-backed deals. We use the combination of Pitchbook industry sector and group codes as industry classification and restrict the sample to industries with at least 15 venture debt deals. We find that industries with the highest reliance on relationships appear to be more R&D intensive. The top industry, chemicals and gases, has 79% of relationship-backed deals, and some of the top industries are related to IT, including semiconductors, hardware, and software, with around 70% of deals having lenders with prior VC ties. The remaining top industries are related to biotech, in medical equipment and pharmaceuticals, with around 65% of relationship-backed deals. Since these industries are innovation-heavy, they tend to be

[8] We also provide market size numbers in Appendix Figure A.1. Venture capital has had the most significant number of deals over the years, equating to around 4,000 deals. Commercial banks have the highest debt amount of 126 trillion USD, given a larger average check size.

more complicated for lenders to obtain information and understand. We observe a high reliance on technology in industries where lenders face asymmetric information.

On the other hand, the industries with the lowest dependence on relationships are more consumer-facing. Many B2C industries, including apparel, restaurants, and non-durables, have around 45% of relationship-backed deals. Client-facing banks have 50% of deals with a relationship. The remaining categories include agriculture materials, packing, energy production, and mining, which are less R&D-heavy and obscure, with 40% deals with relationships. In client-facing industries or low R&D intensity, lenders find it easier to grasp the business and, at the same time, are less dependent on relationships in making investments.

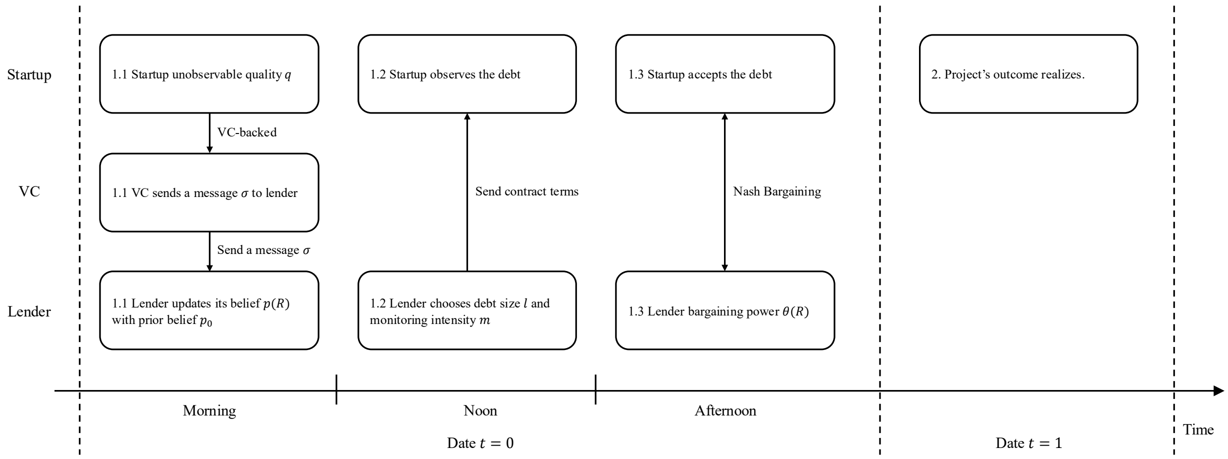
[Insert Table 2 Here.]

In sum, these stylized facts show convincing evidence that the relationship with past investors is an essential consideration of venture lenders, across time, countries, lender type, and industries, and to similar extents as VCs, who are known to rely on networks. They also present interesting heterogeneity: Innovative industries where investors face higher information asymmetry seem to depend more on relationships. Non-bank lenders rely on relationships more than commercial banks, and they have increasingly become a dominant player in the venture debt space. These two aspects of venture debt, prevalence and heterogeneity, motivate us to study how relationships influence venture lenders in every aspect of their investment process, from deal selection to deal crafting, and value creation and exit.

3. A Stylized Framework of Relationship Lending in Venture Debt

To understand the role of the relationship between VC and lender, we develop a stylized framework of relationship lending in venture debt. The model is built around two core features of the venture debt market. First, startups use venture debt to extend runway as bridge financing or to scale a new equity round when equity is costly or when avoiding a down round is valuable (Davis, Morse and Wang, 2020; Gonzalez-Uribe and Mann, 2024).

Figure 3. Timeline of The Model



Notes. This figure presents the timeline of our model.

Second, the repeated relationship that matters is between the VC and the lender, rather than between the startup and the lender. This differs from classic bank relationship lending, which lacks an equity holder or a third party who certifies and monitors on the borrower's behalf (Sharpe, 1990; Rajan, 1992; Bharath et al., 2007; Beck et al., 2018). In venture debt, the VC plays a central role by certifying information that improves the lender's belief about project success, which we call the information channel (De Rassenfosse and Fischer, 2016; Hochberg, Serrano and Ziedonis, 2018). Meanwhile, repeated interaction with the same lender can raise the lender's bargaining power due to switching costs and matching frictions on the VC side, which we call the market power channel (Dougal et al., 2015; Demiroglu, James and Velioglu, 2022), and this force is more pronounced in the venture debt market given the high uncertainty nature of the startup (Hall and Woodward, 2010; Kerr, Nanda and Rhodes-Kropf, 2014).

The model allows us to understand the underlying mechanism through which the relationship between VC and lender facilitates the full life cycle of venture debt lending, including the ex-ante decision, the contract terms, and the post-lending startup performance. These predictions guide the empirical analysis that follows.

3.1. Model Setup and Timeline

We study a startup i, backed by a venture capitalist (VC) v, that seeks venture debt from a lender l to extend its runway (i.e., bridge financing) or to leverage its equity round (i.e., levered financing). The core object is how a relationship between VC v and lender l shapes the lender's belief about the startup's quality and, through that belief, the debt contract.

The model spans two dates, $t = 0, 1$. The timing in date $t = 0$ is sequential but simple. At the start of date $t = 0$, if there is a prior relationship between VC v and lender l, the VC sends a certification message σ to the lender. At midday, anticipating how the price will be set, the lender chooses the loan size L and monitoring intensity m by maximizing its own profit, and the startup observes these contract terms. In the afternoon, the lender and the startup negotiate the price r of the debt contract through Nash bargaining, where the lender's relationship-specific bargaining power is $\theta(R)$. The debt contract (L, r, m) is then finalized and signed at $t = 0$. At $t = 1$, the startup invests in the project, and the project's outcome is realized, which is observed by all parties.

The startup has an investment opportunity that requires external finance. If the project succeeds at $t = 1$, it yields verifiable cash flow X_S. If it fails, it yields X_F. For simplicity, we assume $X_S > X_F = 0$. The success of the project is determined by the startup quality $p_i = \Pr(\text{success}|\mathcal{F}_i) \in (0, 1)$, which is only observed by the startup itself based on its own private information set $\mathcal{F}_i$. Therefore, p_i can be interpreted as the startup's type, with probability p_i being high-quality and $1 - p_i$ being low-quality.

The startup is backed by a VC v who has conducted due diligence and monitors the startup. Based on its information set $\mathcal{F}_v$, the VC forms a private assessment about startup's quality $p_v = \Pr(\text{success}|\mathcal{F}_v) \in (0, 1)$,.

The venture debt lender offers a take-it-or-leave-it debt contract (r, L, m), where $r \geq 0$ is the spread over funding cost which is normalized to zero, $L > 0$ is the loan size, and $m \geq 0$ is monitoring intensity which represents the covenant level or the lender's commitment to monitor the startup's performance. Monitoring has a cost of convex function $c(m)$, with $c'(m) > 0$ and $c''(m) > 0$, and reduces default when the startup is low-quality through a concave salvage function $\phi(m) \in [0, 1)$ with $\phi(0) = 0$, $\phi'(m) > 0$, and $\phi''(m) < 0$.

The lender cannot directly observe the startup quality, but holds a belief about the startup quality, $p_{l,0} = \Pr(\text{success}|\mathcal{F}_l)$ based on its information $\mathcal{F}_l$ collected through its prior experience or due diligence process. With the lender's belief p_l and monitoring intensity m, the probability that the lender believes the startup is high-quality is

$$s_l(p_l, m) = p_l + (1 - p_l)\phi(m).$$

3.2. Relationship between VC and lender

A core feature of our model is the relationship between VC v and lender l. The benefits of a relationship are the information channel, that is, when a prior relationship exists, the VC can credibly certify aspects of the startup that are hard to observe at arm's length.

Let $R \in \{0, 1\}$ indicate whether the lender-VC relationship is previously involved. When $R = 1$, the VC can send a certification message σ to the lender at the beginning of date $t = 0$. The message is always framed as a positive endorsement (e.g., "this is one of our top portfolio companies."). As in practice, VCs rarely transmit negative messages to their lending partners. The VC is not compelled to reveal its complete private assessment q_v. However, messages are disciplined ex post by reputation, as it can be verified once the project outcome is realized at $t = 1$.

From the lender's perspective, the certification message is therefore an informative but not fully reliable signal. Formally, we assume that the message is more likely to be true when the startup ultimately succeeds than when it fails,

$$\Pr(\sigma \text{ is true}|\text{success}) = \gamma_S, \quad \Pr(\sigma \text{ is true}|\text{failure}) = \gamma_F, \quad \gamma_S > \gamma_F.$$

This implies a monotone likelihood ratio $\lambda \equiv \frac{\gamma_S}{\gamma_F} > 1$, meaning that the true certification messages are more likely to come from successful startups.

Given the lender's prior belief $p_{l,0}$, the lender updates its belief when it receives the certification message σ:

$$p_{l,1} = \frac{\gamma_S p_{l,0}}{\gamma_S p_{l,0} + \gamma_F(1 - p_{l,0})} = \frac{\lambda p_{l,0}}{\lambda p_{l,0} + (1 - p_{l,0})}.$$

By the assumption of a monotone likelihood ratio, it also follows $p_{l,1} > p_{l,0}$. Hence, the presence of a relationship shifts the lender's belief upward by $\delta(p_{l,0}, \lambda) = p_{l,1} - p_{l,0} = \frac{\lambda-1}{\lambda\frac{p_{l,0}}{1-p_{l,0}}+1} \in (0, 1 - p_{l,0}]$. In reduced form, we write the lender's belief p_l as

$$p_l(R) = \Pr(\text{success}|\mathcal{F}_l, R) = p_{l,0} + \delta(p_{l,0}, \lambda)R,$$

where $\delta(p_{l,0}, \lambda)$ captures the strength of certification through the relationship, which depends on the lender's prior belief $p_{l,0}$ and the monotone likelihood ratio λ. Therefore, with monitoring intensity m, the lender's contracting belief $s_l(p_l(R), m)$ is given by

$$s_l \equiv s_l(p_l(R), m) = p_l(R) + (1 - p_l(R))\phi(m).$$

3.3. Nash Bargaining

We use backward induction to solve the model. First, we consider the Nash bargaining problem by allowing the venture debt lender and startup to split the total surplus created by the informed contract. Fixed a debt contract (r, L, m) and lender's contracting belief s_l, the lender's expected profit is

$$\Pi_l = \Pi_l(r, L, m; p_l(R)) = s(p_l(R), m)(1 + r)L - L - c(m), \tag{1}$$

and the participation constraint of the lender is $\Pi_l \geq 0$. The startup's expected profit is

$$\Pi_i = \Pi_i(r, L, m; p_l(R)) = s(p_l(R), m)(X_S - (1 + r)L). \tag{2}$$

We assume that there is no outside option for the startup. Therefore, the startup's participation constraint is $\Pi_i \geq 0$. The total surplus from the relationship lending is independent of price r and equals

$$\Pi_{total} = \Pi_{total}(L, m; p_l(R)) = \Pi_l + \Pi_i = s(p_l(R), m)X_S - L - c(m). \tag{3}$$

We first consider the participation constraint of the lender and the startup.

Lemma 1 (Participation Constraint)**.** *There exists a price r that satisfies the participation constraint of the lender and the startup if and only if* $\Pi_{total}(L, m; p_l(R)) \geq 0$.

Lemma (1) shows that if total surplus is negative for a given (L, m), no price can satisfy both parties. If total surplus is non-negative, the feasible pricing interval is nonempty, and Nash bargaining will pick a price inside it. Therefore, for a given belief $p_l \in [0, 1]$, the set of feasible contracts is therefore $\{(L, m) : \Pi_{total}(L, m; p_l) \geq 0\}$. Given (L, m), let's define the value of total surplus at belief p_l as $V(p_l; L, m) = \Pi_{total}(L, m; p_l)$. We then connect asymmetric information to a startup's access to finance in the following lemma.

Lemma 2 (Access to Finance and Asymmetric Information)**.** *The derivative of the value of total surplus $V(p_l; L, m)$ with respect to the belief p_l is given by*

$$\frac{\partial V(p_l; L, m)}{\partial p_l} = (1 - \phi(m))X_s \geq 0. \tag{4}$$

Let $\underline{m}$ satisfies $\phi'(\underline{m})X_s - c'(\underline{m}) = 0$. If $\phi(\underline{m})X_s - c(\underline{m}) < L < X_s$, then $V(0) < 0 < V(1)$, and there exists a unique belief $p_l^* = \frac{L+c(m)-\phi(m)X_s}{(1-\phi(m))X_s}$ such that lending occurs if and only if $p_l \geq p_l^*$.

Here, access to finance improves as the lender becomes more confident about success. A higher belief raises expected cash flows one-for-one in the part not already insured by monitoring, so every candidate contract becomes weakly more attractive. For the startups with high asymmetric information (i.e., low prior belief $p_{l,0}$), the lender's belief is more likely to be close to 0, and the access to finance is more likely to be low. The endpoint conditions compare two extreme cases. When the lender believes the startup will always fail ($p_l = 0$), even the best contract leaves the lender with a negative profit, and so the lending is not visible. When the lender believes the startup will always succeed ($p_l = 1$), lending is visible as long as X_s exceeds the loan size L. Following Lemma (2), we immediately have the following proposition that characterizes the relation between access to finance, asymmetric information, and the relationship.

Proposition 1 (Access to Finance and Relationship)**.** *The derivative of the value of total surplus $V(p_l; L, m)$ with respect to the relationship R is given by*

$$\frac{\partial V(p_l; L, m)}{\partial R} = (1 - \phi(m))X_s\delta(p_{l,0}, \lambda) \geq 0, \tag{5}$$

where the equality holds when $\phi(m) = 1$. Moreover,

$$\frac{\partial^2 V(p_l; L, m)}{\partial p_{l,0} \partial R} = -(1 - \phi(m)) X_s \frac{\lambda(\lambda - 1)}{(\lambda p_{l,0} + 1 - p_{l,0})^2} \leq 0, \tag{6}$$

A VC-lender relationship shifts the lender's belief by $\delta(p_{l,0}, \lambda)$ through certification. Since the value function $V(p_l; L, m)$ is increasing in p_l, in the cross-section, the total surplus is more likely to be positive for any given (L, m) for a higher belief. Therefore, the relationship weakly expands the feasible set of contracts.

For the second part of Proposition (1), we show that the second derivative with respect to R and $p_{l,0}$ is negative. Here, $p_{l,0}$ represents the lender's prior belief on the startup's quality. The more asymmetric information about the startup, the lower the lender's prior belief $p_{l,0}$. Therefore, the negative second derivative implies that the relationship can offset the adverse effect of asymmetric information.

The lender and startup split the total surplus from the relationship lending through Nash bargaining over the price r, holding the loan size L and monitoring intensity m fixed. Let $\theta(R) \in [0, 1]$ be the lender's bargaining power. It increases in the relationship, where $\theta(1) > \theta(0)$. So the Nash bargaining problem becomes

$$\begin{aligned} \max_{r} \quad & \Pi_l(L, r, m; p_l(R))^{\theta(R)} \Pi_i(L, r, m; p_l(R))^{(1-\theta(R))} \\ \text{s.t.} \quad & \Pi_l(L, r, m; p_l(R)) \geq 0 \quad \text{and} \quad \Pi_i(L, r, m; p_l(R)) \geq 0. \end{aligned} \tag{7}$$

On the feasible set in Lemma (1), the first-order condition implies that under the optimal price r^* solves the following equation

$$(1 - \theta(R)) \Pi_l(L, r, m; p_l(R)) = \theta(R) \Pi_i(L, r, m; p_l(R)).$$

Rearranging the equation, we have the lender's profit is $\Pi_l = \theta(R) \Pi_{total}$ and the startup's profit share is $\Pi_i = (1 - \theta(R)) \Pi_{total}$. Now we can solve for the optimal price r^* as follows:

Lemma 3 (Optimal Debt Spread)**.** *Given the Nash bargaining problem in (7) and the lender's* *bargaining power $\theta(R) \in [0,1]$, the optimal price r^* is given by*

$$r^* = r^{BE} + \theta(R)\mu = (1-\theta(R))r^{BE} + \theta(R)r^{FC} \tag{8}$$

where $r^{BE} = \frac{L+c(m)}{s(p_l(R),m)L} - 1$ is the break-even price, $r^{FC} = \frac{X_S}{L} - 1$ is the feasibility cap, and $\mu = \frac{\Pi_{total}}{s(p_l(R),m)L} = r^{FC} - r^{BE}$ is the markup. The optimal price r^* always satisfies the participation constraint of both lender and startup.

Lemma (3) shows that the optimal price r^* is a convex combination of the break-even price r^{BE} and the feasibility cap r^{FC}. When the lender's bargaining power is zero (i.e., $\theta(R) = 0$) and all the surplus goes to the startup, the optimal price r^* equals the break-even price r^{BE} of the lender. In contrast, when the lender's bargaining power is one (i.e., $\theta(R) = 1$) and all the surplus goes to the lender, the optimal price r^* equals the feasibility cap r^{FC}. Lemma (3) also implies that the participation constraint of both parties is always satisfied because the optimal price r^* is always bounded by the feasibility cap r^{FC} and the break-even price r^{BE}.

Next, we present the proposition that characterizes the comparative statics of the optimal price r^* with respect to the relationship between VC and lender.

Proposition 2 (Optimal Debt Spread and Relationship)**.** *Given the Nash bargaining problem in (7) and the lender's bargaining power $\theta(R) \in [0,1]$, the derivative of the optimal price r^* with respect to the relationship between VC and lender R is given by*

$$\frac{\partial r^*}{\partial R} = (1-\theta(R))\frac{\partial r^{BE}}{\partial R} + \theta'(R)(r^{FC} - r^{BE}). \tag{9}$$

Moreover,

$$\frac{\partial r^{BE}}{\partial R} = -\frac{L+c(m)}{s(p_l(R),m)^2 L}(1-\phi(m))\delta(p_{l,0},\lambda) \leq 0. \tag{10}$$

The proposition isolates two forces of the relationship on the optimal price r^*. The first force is the information channel, which lowers the optimal spread r^*. It increases the lender's belief about the startup quality by $\delta(p_{l,0},\lambda)$, which further increases the lender's contracting probability $s(p_l(R),m)$ and reduces the break-even price r^{BE}. The second force is the market-power channel, which raises the optimal spread r^*. If $\theta'(R) > 0$, the relationship increases the lender's bargaining weight and therefore the markup component $r^{FC} - r^{BE}$. The net effect depends on which force dominates.

3.4. Lender's Optimal Decision

Because the Nash bargaining splits the total surplus in fixed shares, the lender's profit Π_l is always proportional to the total surplus Π_{total}. So the lender's optimal decision is to choose the optimal loan size L^* and monitoring intensity m^* to maximize the total surplus Π_{total}:

$$\max_{L,m} \Pi_{total} = s(p_l(R), m)X_S - L - c(m). \tag{11}$$

For the loan size L, the first-order condition gives

$$\frac{\partial \Pi_{total}}{\partial L} = -1 < 0.$$

The total surplus is strictly decreasing in the loan size L, and the lender chooses the smallest feasible loan size $L^* = L_{min}$ that satisfies the participation constraint in Lemma (1). For the monitoring intensity m, the first-order condition gives

$$\frac{\partial \Pi_{total}}{\partial m} = (1 - p_l(R))X_S\phi'(m^*) - c'(m^*) = 0.$$

Intuitively, the lender chooses the monitoring intensity m^* that balances the marginal benefit of monitoring and the marginal cost of monitoring. The marginal benefit of monitoring is $(1 - p_l(R))X_S\phi'(m)$, which is the expected increase in the startup's success profits due to the monitoring. Putting together, we have the following lemma that characterizes the lender's optimal loan size and monitoring intensity.

Lemma 4 (Optimal Loan Size and Monitoring Intensity)**.** *Given the lender's problem in* (11) *and participation constraint in Lemma* (1)*, the lender's optimal loan size L^* is given by*

$$L^* = L_{min} \equiv \phi(\underline{m})X_s - c(\underline{m}), \tag{12}$$

where $\underline{m}$ *satisfies* $\phi'(\underline{m})X_s - c'(\underline{m}) = 0$*. The lender's optimal monitoring intensity* m^* *is uniquely determined by*

$$(1 - p_l(R))X_S\phi'(m^*) - c'(m^*) = 0. \tag{13}$$

Next, we provide the comparative statics of the lender's optimal loan size and monitoring intensity with respect to the relationship between VC and lender R.

Proposition 3 (Optimal Contract Terms and Relationship)**.** *Given the lender's problem in* (11) *and participation constraint in Lemma* (1)*, the derivative of the lender's optimal loan size* L^* *and monitoring intensity* m^* *with respect to the relationship* R *is given by*

$$\frac{\partial L^*}{\partial R} = 0, \tag{14}$$

and

$$\frac{\partial m^*}{\partial R} = \frac{\delta(p_{l,0}, \lambda)X_s\phi'(m^*)}{(1 - p_l(R))X_S\phi''(m^*) - c''(m^*)} < 0. \tag{15}$$

In our model, the lender's optimal loan size L^* is not affected by the relationship between VC and lender R because the lender's optimal loan size L^* is independent of the relationship.[9] The model also delivers a precise contract term prediction that relationships reduce hard monitoring and covenants. This is because the relationship R increases the lender's belief about the startup quality by $\delta(p_{l,0}, \lambda)$, which substitutes the need for monitoring.

After characterizing the lender's optimal decision, we turn to the startup's profit after accepting the lender's debt contract. As in the lender's problem, the startup's profit is also proportional to the total surplus Π_{total}, $\Pi_i = (1 - \theta(R))\Pi_{total}$.

Proposition 4 (Startup's Profit and Relationship)**.** *Given the optimal contract terms in Lemma* (4)*, the derivative of the startup's profit* Π_i *with respect to the relationship* R *is given by*

$$\frac{\partial \Pi_i}{\partial R} = (1 - \theta(R))(1 - \phi(m^*))X_s\delta(p_{l,0}, \lambda) - \theta'(R)\Pi_{total}(L^*, m^*; p_l(R)). \tag{16}$$

[9] In fact, if we introduce the risk component into the model (e.g., risk averse lender or maximum expected loss constraint), the lender will face a trade-off between higher loan size and lower monitoring intensity, which will affect the lender's optimal loan size L^*.

The relationship affects Π_i through the same two channels as in spread r^* in Proposition (2). First, the first term in Proposition (2) is the information channel. It increases the startup's profit by increasing the lender's belief about the startup's quality, thereby increasing the total surplus. The extra expected surplus is shared with the startup. The second term represents the market power channel, which reduces the share of the total surplus to the startup and thus the startup's profit. The net effect is positive whenever the information channel dominates the market power channel. In the following corollary, we show that under the participation constraint condition in Lemma (1), relationships can raise the spread and still benefit the startup.

Corollary 1 (Market Power, Loan Spread, and Startup's Profit)**.** *Given the optimal contract terms in Lemma* (4) *and participation constraint condition in Lemma* (1)*, if the lender's bargaining power* $\theta(R)$ *satisfies*

$$\frac{L^* + c(m^*)}{s(p_l(R), m^*)} \frac{(1-\phi(m^*))\delta(p_{l,0}, \lambda)}{\Pi_{total}(L^*, m^*; p_l(R))} < \frac{\theta'(R)}{1-\theta(R)} < X_s \frac{(1-\phi(m^*))\delta(p_{l,0}, \lambda)}{\Pi_{total}(L^*, m^*; p_l(R))}, \tag{17}$$

then

$$\frac{\partial \Pi_i}{\partial R} > 0 \quad \textit{and} \quad \frac{\partial r^*}{\partial R} > 0. \tag{18}$$

The two bounds pin down how much the lender's bargaining weight can rise with the relationship. Here, $\frac{\theta'(R)}{1-\theta(R)}$ can be interpreted as the hazard rate associated with bargaining power $\theta(R)$. It captures the rate at which an incremental strengthening of the relationship R converts the remaining startup share $(1-\theta)$ into lender markup. The left bound is the minimum hazard rate needed for the spread r^* to rise, where the markup must be strong enough to offset the fall in the competitive component r^{BE}. The right bound, as the maximum hazard rate, ensures the markup does not rise so much that it absorbs the information-driven surplus and leaves the startup worse off. The participation constraint condition ensures the interval is nonempty, since $\Pi_{\text{tot}} = s(p_l(R), m^*)X_S - L^* - c(m^*) \geq 0$ and therefore the right bound is at least as large as the left bound.

3.5. Propositions and Predictions

The model presented above yields a set of testable predictions that guide our empirical analysis. These predictions highlight how a VC-lender relationship shapes the life cycle of a venture debt deal, including the ex-ante decision, the contract terms, and the startup's subsequent performance.

First, as in Proposition (1), our model shows that the presence of a relationship expands the feasible set of contracts by raising the lender's belief, which offsets the negative effect of asymmetric information. This leads to our first empirical hypothesis:

Hypothesis 1. *The VC-lender relationship increases the probability that a startup obtains venture debt and offsets the negative association between information frictions and access.*

Second, as in Proposition (3), the model predicts that the relationship reduces the monitoring intensity and hard restrictions in the debt contract. This gives our second empirical hypothesis:

Hypothesis 2. *The venture debt contract is less monitoring-intensive and has fewer hard restrictions when the lender has a relationship with the VC.*

Third, Proposition (2) shows that the spread reflects two opposing forces, where the information channel lowers the competitive component and relationship-specific bargaining power raises the markup. Hence, we have our two competing sub-hypotheses:

Hypothesis 3a. *The venture debt spread is lower when the lender has a relationship with the VC, as the information channel dominates the market power channel.*

Hypothesis 3b. *The venture debt spread is higher when the lender has a relationship with the VC, as the market power channel dominates the information channel.*

Finally, similar to the prediction about loan spread, the model predicts that the relationship affects the startup's growth through the same two channels, as in Proposition (4) and Corollary (1). The information channel increases the startup's growth by increasing the lender's belief about the startup's quality and thus increasing the total surplus. In contrast, the market power channel reduces the startup's growth by reducing the share of the total surplus to the startup. This leads to the last testable implication:

Hypothesis 4a. *The startup's growth is higher when the lender has a relationship with the VC, as the information channel dominates the market power channel.*

Hypothesis 4b. *The startup's growth is lower when the lender has a relationship with the VC, as the market power channel dominates the information channel.*

Together, these four predictions form a coherent empirical framework of relationship lending in venture debt. In the following sections, we will test these hypotheses using our data. We will confirm our hypotheses about access and contract terms, as they have clear directional tests. For the spread and startup's growth, we will distinguish the two competing channels of the relationship.

4. Venture Debt Relationships and Ex-ante Decision

In this section, we study the ex-ante selection of venture lenders into debt deals. We show evidence that the relationship with venture capitalists plays an essential role in venture lenders' decisions to allocate loans to startups, increasing the probability of getting venture debt deals compared to firms that are unlikely to get venture debt without this relationship. First, we show that, among a set of firms matched on industry, country, and size, firms with high asymmetric information from the lender's perspective are less likely to get a venture debt deal because they require high verification needs of firms' unobserved quality. Consistent with Hypothesis 1 in our theoretical framework, we further show that if the lender has relationships with the firm's past VC investors, it eliminates the adverse effect in high-asymmetric-information companies, as we see a significantly higher probability for the firm to get venture debt funding. Second, we conduct a cross-industry comparison of the effect of relationship and present that in industries with high R&D intensity, relationship is more important in obtaining a venture debt deal, again consistent with the prediction. Finally, within venture debt deals, we see that deals where lenders have relationships with VCs have lower profitability. This is consistent with our prediction that with stronger relationships with VCs, venture lenders rely less on hard information to select portfolio companies.

4.1. Relationship and Asymmetric Information

We first analyze how venture lenders' relationships with venture capitalists are related to startups' likelihood to obtain venture lending, and confirm Hypothesis 1 in our theoretical framework that the relationship increases the set of firms getting venture debt and offsets the adverse effects from asymmetric information. We test this using the matched control group in the same country, industry, and financing stage, detailed in Section 2.2.4. For each venture debt deal, we use the complete matched set of control firms as the consideration set when a venture lender considers which companies to lend money to. Therefore, we mimic a lender's decision where she wants to invest in a particular country and industry, at a specific stage of financing, and select a firm to invest in. We study how a firm's level of asymmetric information and the lender's relationship with the firm's investors affect its likelihood of getting venture lending. For this purpose, we use various measures of asymmetric information at the firm-quarter level and compute the relationship between each lender in this deal and each matched company's previous investors. We estimate the following regression at the deal-lender-company level:

$$\begin{aligned} I(\text{VD Deal})_{d,l,i} = {} & \beta_1 \text{AsymInfo}_{d,i} \times I(\text{Relationship})_{d,l,i} + \beta_2 \text{AsymInfo}_{d,i} \\ & + \beta_3 I(\text{Relationship})_{d,l,i} + \gamma \text{Controls}_{d,i} + \alpha_{d,l} + \varepsilon_{d,l,i} \end{aligned} \tag{19}$$

For each treated and matched control firm i in deal d, we calculate several measures to approximate asymmetric information from patent portfolio, news coverage, and distance. We use three patent measures: the cumulative patent count, citations, and citation-weighted patents. Firms with more patents are highly innovative but also highly informatively asymmetric at the same time. We use negative cumulative news, as firms with more news face fewer information asymmetries. Finally, we compute the distance between the lender and the company as the distance between the headquarters city coordinates, as there is more asymmetric information if the company is farther away. $I(\text{Relationship})_{d,l,i}$ equals 1 if lender i of the venture debt deal d has at least one previous working relationship with any previous investors of company i. We control for log employment, log age in quarters, and log value of cumulative financing amount. We also control for deal×lender fixed effects to effectively compare candidate firms in the same deal with the same lender.

[Insert Table 3 Here.]

Table 3 reports the results of these regressions. First, we see a strong positive coefficient on the relationship indicator. If the lender has past relationships with the firm's investors, the firm is 21-26% more likely to obtain venture debt from the lender. This is consistent with Proposition 1, where the relationship shifts upwards the lender's belief about startup quality through verification and expands the feasible set of portfolio companies.

Second, across all measures of asymmetric information, we find that firms with a higher level of asymmetric information are less likely to receive venture loans. This is consistent with Lemma 2 in our theory. Firm quality is unobservable to lenders, and lenders face verification costs to filter out lemons. Higher asymmetric information drives down lenders' confidence about a startup's success. With more costly verification of firm quality, it is less likely that the lender will lend to the company.

Third, and most importantly, when we interact asymmetric information with the relationship indicator, we find positive coefficients across all columns. Having relationships with investors helps mitigate the cost of high asymmetric information and makes the lender more willing to lend. Moreover, the coefficient on the interaction term is higher than the negative coefficients on the asymmetric information. In the table, we test the sum of the two coefficients to be statistically significant for almost all definitions of asymmetric information. This aligns with Proposition 1: relationships with VCs completely offset the adverse effects of asymmetric information. Lenders are willing to invest in companies with high information asymmetry that they would not otherwise invest in if they have relationships with the firm's venture capital investors.

4.2. Industry R&D Intensity

Our previous exercise compares the likelihood of obtaining venture lending among firms within the same industry but with different levels of asymmetric information. In this section, we conduct a cross-industry analysis to determine which industries venture lenders rely more heavily on relationships with venture capital to make deals. Using the same treated and matched control sample, we interact the relationship with industry-level R&D intensity. We hypothesize that industries with high R&D intensity are more prone to asymmetric information. Lenders operating in such industries are more dependent on relationships with VC to alleviate information cost and select deals. To test this hypothesis, we run the following regression at the deal-lender-company level.

$$\begin{aligned} I(\text{VD Deal})_{d,l,i} = \beta_1 \text{R\&D Intensity}_{ind} \times I(\text{Relationship})_{d,l,i} \\ + \beta_3 I(\text{Relationship})_{d,l,i} + \gamma \text{Controls}_{d,i} + \alpha_{d,l} + \varepsilon_{d,l,i} \end{aligned} \tag{20}$$

We measure R&D intensity as either the ratio of R&D expense over total assets or to total sales. We take the mean or median of R&D intensity among public firms in the Compustat database to get industry R&D intensity measures. Again, for treated and matched firms in the same industry, country, and financing stage, $I(\text{Relationship})_{d,l,i}$ equals one if lender i of the venture debt deal d has at least one previous working relationship with any previous investors of company i. We control for log employment, log age in quarters, and log value of cumulative financing amount. We also control for deal×lender fixed effects to effectively compare candidate firms in the same deal with the same lender.

[Insert Table 4 Here.]

In Table 4, we find that the relationship again increases the likelihood of a company obtaining venture loans. If the lender has past relationships with the startup's past investors, the startup is unconditionally 16-24% more likely to get venture debt from the lender. More importantly, relationships become much more critical in industries with high R&D intensity. Across all four definitions of industry-level R&D intensity, we find that lenders in industries with high R&D intensity depend more heavily on the relationship with the previous investors of the firm in striking deals. In these highly innovative industries, lenders often lack the necessary expertise to assess the quality of startups. And thus, they rely more strongly on a relationship with venture capitalists as a verification device to select good deals.

4.3. Firm Characteristics

In this section, we propose and test a hypothesis that relationships with VC alleviate the negative impact of asymmetric information and increase the possible set of borrowers from venture debt. An alternative story, however, is that venture capitalists, instead of providing a certification message via a relationship, offer venture lenders that they have a relationship with high-quality projects. In the context of our theoretical framework, this means that the relationship does not work through the channel of shifting the lender's posterior belief, but instead selects projects on which lenders have high prior belief. We argue against this alternative hypothesis by demonstrating that firms that relationship-based venture lenders take on are *not* of *a prior* good quality.

To examine this, we analyze a range of firm characteristics measured prior to the focal deal date by estimating deal-level regressions of firm characteristics on an indicator for the lender-VC relationship.

$$\text{Characteristics}_{d,i} = \beta_1 I(\text{Relationship})_d + \gamma\text{Controls}_{d,i} + \alpha_{I(i),T(d)} + \alpha_{C(i),T(d)} + \alpha_{Round(d)} + \varepsilon_{d,i}. \quad (21)$$

The firm characteristics we consider include the log revenue, net income margin (net income divided by revenue), EBITDA margin (EBITDA divided by revenue), labor productivity (revenue per employee), the log number of cumulative trademarks, and the log number of cumulative patents. All these firm characteristics measures are already realized at the time of the deal. $I(\text{Relationship})_d$ is the relationship between the lenders involved in the venture debt deal d and the previous investors of the firm. We control for a set of covariates, including the lagged log number of employees, the lagged log cumulative financing amount, the lagged log age, an indicator of whether the startup is in the same city as the lenders, and the log distance between the startup and the lenders. $\alpha_{I(i),T(d)}$ is industry($I(i)$-year($T(d)$) fixed effects, $\alpha_{C(i),T(d)}$ is country($C(i)$-year($T(d)$) fixed effects, and $\alpha_{Round(d)}$ is deal-round fixed effects. Standard errors are clustered at the startup level.

[Insert Table 5 Here.]

We present the results in Table 5. Across different measures of firms' current characteristics, we find no statistically significant differences between startups backed by relationship lenders and those that are backed by non-relationship lenders. Profitability measures such as revenue, EBITDA, and net income, as well as the number of existing product trademarks and patents, are not significantly different for startups with relationship-backed lenders compared to those with other lenders. These null results indicate that, at the time of the deal, relationship lenders do not systematically invest in firms that are observably higher or lower quality in terms of profitability or commercialization status. This suggests that, on observable current firm characteristics, there is no clear pattern or selection effect associated with the presence of a relationship between the lender and VC.

5. Venture Debt Relationship, Contract Terms, and Price

In this section, we study how the relationship affects venture lenders' decisions in the deal structure and pricing. We find two sets of empirical evidence that align with our theoretical framework. First, we find that deals whose lenders have a relationship with past VCs tend to impose less monitoring than deals without a relationship. These loans are more likely to be unsecured, cov-lite, and convertible. They tend to be senior claims without collateral. Second, we study the equilibrium spread charged on the loans. Our framework identifies two competing forces that lead to opposite predictions. Spreads may be higher as lenders get more bargaining power in the relationship. At the same time, spread could also be lower as the relationship resolves information asymmetry, increases lender demand, and reduces the breakeven price. Using various specifications, we consistently find that relationship-backed deals have higher spreads, suggesting that the market power channel dominates the information channel.

5.1. Empirical Setup

Cross-Sectional Analysis To investigate the crafting stage of venture debt deals, we use a novel deal-debt facility-lender level data set that contains detailed information on debt size, maturity, and terms. Each venture debt deal may consist of several debt facilities, each of which is a separate type, such as revolving credit or term loans, with different terms. Each facility can be funded by multiple lenders. Since each facility has its own amount and terms, we run our analyses at the deal-facility level. As before, we define a deal-facility level relationship as having at least one lender of this facility with a relationship with the startup's previous investors. We run the following regressions with different debt terms and prices:

$$Y_{d,f,i} = \beta_1 I(\text{Relationship})_d + \gamma \text{Controls}_{d,i} + \alpha_{I(i),T(d)} + \alpha_{C(i),T(d)} + \alpha_{round(d,f)} + \varepsilon_{d,f,i}. \tag{22}$$

$Y_{d,f,i}$ is the contract terms or spread for startup i who received facility f in a venture debt deal d. The main independent variable, $I(\text{Relationship})_d$, is the relationship between the lenders involved in the venture debt deal d and the startup's prior investors. We control for a set of covariates, including the lagged log number of employment, lagged log value of cumulative financing amount, lagged log value of age, an indicator of whether the startup is in the same city as the lenders, and the log value of distance between the startup and lenders. We control for a range of fixed effects: $\alpha_{I(i),T(d)}$ is industry($I(i)$-year($T(d)$) fixed effects, $\alpha_{C(i),T(d)}$ is country($C(i)$-year($T(d)$) fixed effects, and $\alpha_{round(d,f)}$ is deal-facility round fixed effects. In the most stringent specification, we compare terms in debt facilities for deals in the same industry year, same country year, and same debt round.

Instrumental Variables A key empirical challenge in our analysis is potential endogeneity in the assignment of relationship lenders to deals. The selection of lenders may be correlated with unobserved characteristics of the startup, the deal, or the VC investors. For example, VC investors might refer their most promising startups to lenders with whom they have relationships, thereby preserving valuable ties and reputation. Conversely, VCs could turn to relationship lenders to help low-quality startups, providing access to credit that would otherwise be unavailable. This creates a concern that the observed correlations between relationship lending and deal outcomes could reflect unobserved differences in the firm quality rather than a causal effect of the relationship itself.

Ideally, we would want some exogenous variation in the lender-selection process, such as an external rule or institutional feature that randomizes lender assignment to deals. Since such exogenous variation is rarely available in real-world settings, we follow the approach in Ivashina and Kovner (2011) to address endogeneity via an instrumental variables (IV) strategy.

Our IV exploits variation in the concentration of VCs' prior lending relationships before the focal deal. More specifically, the instrument is computed as the Herfindahl-Hirschman Index (HHI) of VCs' prior lending relationships over the past ten years. Here, the idea is that VCs whose previous lending relationships are highly concentrated among a small set of lenders have less bargaining power with those lenders (Rajan, 1992). To restore bargaining leverage, such VCs are incentivized to diversify and expand their relationships with new lenders in subsequent deals. Therefore, a VC with concentrated past relationships should be less likely to select a relationship lender for a new deal. Importantly, our instrument is constructed solely from the VC's prior relationship structure, which should be exogenous to unobserved characteristics of the current startup, deal, or lender that might affect outcomes. In other words, conditional on observed controls, the VC's historical lender concentration influences deal outcomes only through its effect on the probability of selecting a relationship lender, not through other unobserved channels.

5.2. Relationship and Contract Terms

Using this specification, we study the lender's decision when drafting a deal for startups. Specifically, we examine various features of deal terms, including the type of loan, the presence and nature of collateral, and the loan's seniority. Table 6 reports the results using both OLS and IV regressions.

We first observe that, consistent with Hypothesis 2 in our theoretical framework, when lenders have relationships with past VCs, the venture debt contract has lower monitoring intensity. Compared with deals without a prior relationship, relationship-backed loans are 5% less likely to be structured as term loans and 2% more likely to be structured as revolving credit. Additionally, the relationship lenders provide the startup with more flexibility and fewer restrictions, as relationship-backed deals are 16% less likely to be secured and 6% less likely to be first-lien loans. These differences are economically meaningful, given that, on average, 22% of venture debt is secured and only 3% is structured as first liens. For all IV specifications, the first-stage coefficients for our instrument are negative and highly significant, with F-statistics consistently ranging between 620 and 750, confirming the instrument's strength and validity.

[Insert Table 6 Here.]

Appendix Table A.3 reports results on loan amounts and maturities. We see that lenders with relationships tend to offer smaller loans, although this effect is not statistically significant in the IV specifications. This finding aligns with our stylized framework, which predicts that optimal loan size is independent of optimal monitoring intensity. Regarding maturity, we find that deals backed by relationship lenders are more likely to have shorter maturities.

5.3. Relationship and Loan Price

We then study how the equilibrium loan price is related to the lender's relationships with past VC. This analysis corresponds to the Nash bargaining stage in our theoretical framework, during which the lender negotiates the loan price with the startup. In our framework, the relationship has two competing forces on loan prices, leading to opposite predictions. The first channel is the *market power* channel. Lenders with a relationship have more bargaining power when negotiating the deal with the startup and can thus charge a higher spread. The second channel is the *information* channel. Lenders with prior VC ties get certification of a startup's quality, which influences their posterior beliefs about the startup's success. This leads to higher demand from the lender and a higher contracting probability, which reduces the loan price. We test which channel dominates in venture debt deal negotiations. If the information channel dominates, Hypothesis 3a holds, and the relationship should be correlated with lower spreads. In contrast, if market power channel dominates, then Hypothesis 3b holds, and the relationship should be correlated with higher spreads.

[Insert Table 7 Here.]

We run regressions of deal-facility-level loan spreads on lenders' relationships with past investors. We obtain consistent results by exploiting various specifications in Table

7. In Column (1), without any controls, we see that having a relationship increases the equilibrium spread by 84 basis points. If we include firm observables in Columns (2), employment, financing amount, age, and physical distance between lender and borrower, having relationships increases the equilibrium spread by 142 basis points. One potential concern is that the loan spread may differ across different types of loans. To address this concern, we further control for loan characteristics in Column (3), including indicators for whether the loan is a term loan, a revolving credit, or secured. The results are consistent with the previous findings. This increase remains robust when we include various fixed effects in Column (4). When comparing deal facilities within the same country, year, same industry year, and same debt round, spreads are 88 basis points higher when lenders have relationships with startups' previous investors. In the last column, we use an instrumental variables specification to address endogeneity in the relationship. The first-stage coefficient is negative and statistically significant, with an F-statistic of 100. The results are consistent with the previous findings, with a coefficient of 149 basis points. The economic magnitude is quite large, accounting for 19% (= 149/802) of the sample mean.

Across all specifications, we consistently find that lenders with established relationships with past investors can charge a higher spread on venture debt deals. This indicates that the market power channel dominates in the venture debt setting. This phenomenon is consistent with BDCs' ability to charge higher spreads in the private direct lending market (Davydiuk et al., 2024), but is distinct from relationship lending in banks (Bharath et al., 2011).

5.4. Loan Price, Outside Options, and Agency Conflict

Having established in the previous section that the market power channel dominates in venture debt negotiations over the spread, we now investigate the mechanisms through which relationships enhance lenders' bargaining power. We explore two potential channels: outside options and VC-startup agency conflicts.

Outside Options. To study the underlying mechanism of the market power channel, we first examine how outside options affect the higher spread charged on relationship-backed loans. In a competitive lending market, startups and their VCs would be expected to seek out looser contracts by other lenders if the lender charges a higher spread. In equilibrium, one might expect the observed contracts to be invariant to relationship status. The relationship banking literature, however, has shown that exclusive bank-borrower relationships create hold-up opportunities for lenders to extract rents from borrowers (Sharpe, 1990; Petersen and Rajan, 1995; Schenone, 2010; Ioannidou and Ongena, 2010). Therefore, we test the connection between the breadth of outside options and the spread charged on relationship-backed loans.

Panel (a) of Table 8 shows the results. In Column (1), we capture the breadth of outside options by the number of lenders the VCs have worked with in the past ten years and interact the relationship measure with a dummy variable for which startups have the outside options below the bottom 30th percentile level. We find that the interaction term is positive and statistically significant, with a coefficient of 129 basis points. In Columns (2) and (3), we further measure the breadth of outside options by whether the VC has no lending business and the number of local lenders in the same country and industry. We find that the interaction terms are all significantly positive. Relationship lenders exploit their informational advantage and reduced competition to charge higher spreads when a startup's VCs and the startup itself have fewer alternative lenders, consistent with the market power channel.

[Insert Table 8 Here.]

Agency Conflicts. The second underlying mechanism we explore is whether agency conflicts between VCs and startups allow relationship lenders to extract higher spreads. So far, we have assumed that the VC and the startup are aligned. However, in reality, the VC and the startup may have conflicting interests, as the VC is optimizing for the long-term value of its entire portfolio while the startup is optimizing only its own value. Therefore, VCs may tolerate lenders' higher prices because they value the relationship capital for future portfolio companies more than the immediate cost to the current startup. This incentive should be strongest for VCs who are repeat players in the venture debt market.

In Panel (b) of Table 8, we proxy for VC pressure and repeat-player status using the number of VC investors in Column (1), VCs' age in Column (2), and VCs' portfolio size in Column (3). We find that the spread charged on relationship-backed loans is significantly higher when VCs have greater influence or are more established repeat players. The interaction term between the relationship indicator and high VC pressure ranges from 122 to 144 basis points and is statistically significant across all specifications. This evidence supports the agency conflict channel, in which VCs strategically trade off higher spreads on their current portfolio companies for relationship benefits that accrue across their broader portfolio of investments.

6. Venture Debt Relationship and Startup Outcomes

After examining the contract terms in the previous section, we turn to consequences for startup growth. The model developed in Section 3 delivers two opposing predictions about startups' growth. The information channel as in Hypothesis 4a implies that the relationships expand total surplus and raise the startup's payoff by easing verification. However, the market power channel in Hypothesis 4b predicts lower startup payoffs as relationship lenders extract rents. We evaluate these two forces by examining follow-on financing, exits, and innovation after the focal venture–debt deal. We conclude by reviewing heterogeneity in innovation strategy, asking which types of innovation strategies startups pursue to achieve subsequent growth.

6.1. Empirical Strategy

To identify the effect of venture debt relationships on subsequent startup outcomes, we compare treated startups that received a venture debt deal in a given quarter with carefully matched controls constructed through the CEM procedure in Section 2.2.4. For each treated startup, we select control firms that are highly comparable on pre-treatment observables, including exact matches on country, industry, and financing stage, as well as coarsened matches on age, cumulative financing, and employment. Among firms that satisfy these criteria, we choose the ten nearest neighbors based on absolute differences in age, cumulative financing, and employment.

Formally, we estimate the following stacked triple-difference specification (Cengiz et al.,

2019) on a deal(d)-startup(i)-quarter(t) panel. We consider a five-year window around the deal quarter, with a two-year pre-event window and a three-year post-event window.

$$
\begin{aligned}
Y_{d,i,t} = {} & \beta_1 \text{Treated}_{d,i} \times \text{Post}_{d,t} \times I(\text{Relationship})_d \\
& + \beta_2 \text{Treated}_{d,i} \times \text{Post}_{d,t} + \gamma \text{Controls}_{d,i,t} + \alpha_{d,i} + \alpha_{d,t} + \varepsilon_{d,i,t}.
\end{aligned} \tag{23}
$$

Here, $Y_{d,i,t}$ is the outcome of interest for startup i in quarter t in the venture debt event d. For financing activities, we consider an indicator for obtaining a VC round and the log amount raised. For exit events, we use an indicator for whether the startup i goes to an IPO, is acquired, or files for bankruptcy in quarter t. For innovation activities, we 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.

The key variable, $I(\text{Relationship})_d$, is the relationship between the lenders involved in the venture debt deal d and the treated startup's prior investors, defined at origination and held fixed across startups and time. $\text{Treated}_{d,i}$ equals one for the treated startup in venture debt deal d and zero for its matched control groups. $\text{Post}_{d,t}$ equals one for quarters in the three-year post-event window $[t, t+12]$.

Thus, the coefficient β_2 is the baseline difference-in-difference effect, capturing the average treatment effect of receiving venture debt for treated firms relative to their matched controls. The triple-difference coefficient β_1 captures the incremental impact of receiving relationship-backed venture debt, compared to receiving non-relationship venture debt.

We require the startup to be observed for at least two years before the deal in the pre-event window to ensure balanced pre-trends within matched sets. We control for the log number of employment, the log value of cumulative financing amount, and the log value of age in the regression. $\alpha_{d,i}$ are deal-startup fixed effects and $\alpha_{d,t}$ are deal-quarter fixed effects. Standard errors are clustered at the startup level.

6.2. Startup Future Financing

We begin by investigating the effects of venture debt relationships on startups' future financing, focusing on the likelihood and magnitude of follow-on financing rounds. Future financing rounds are crucial indicators of startup growth as they reflect a startup's ability to attract additional capital. This is particularly important in the context of venture debt, as 73% of venture debt deals are flagged as bridge financing deals. The primary goal of these deals is to fill the gap between a startup's current financing needs and its next financing round, thereby supporting growth or avoiding a potential downround (Morse, 2024).

[Insert Table 9 Here.]

Table 9 presents the results. We first focus on the average difference-in-difference effects of receiving venture debt on future financing. Columns (1) and (3) show that venture debt startups are less likely to obtain a subsequent VC round and raise smaller amounts. Quantitatively, receiving venture debt reduces the likelihood of obtaining a follow-on VC round by 1.6 percentage points, relative to a sample mean of 9.3 percentage points. Similarly, the log amount raised in the follow-on VC round is six percentage points lower. In Column (5), we further examine the effect of receiving venture debt on the likelihood of obtaining a follow-on equity round with existing VCs. We find that receiving venture debt reduces the likelihood of a follow-on equity round from existing VCs, accounting for 20% (= 0.008 / 0.041) of the sample mean. These adverse effects are consistent with the fact that venture debt temporarily substitutes for equity financing to support startup growth.

Columns (2) and (4) add the relationship interaction term. Relationship-backed venture debt significantly mitigates the adverse effects of venture debt on the equity fundraising outcomes. Specifically, the likelihood of obtaining a follow-on VC round is 2.1 percentage points higher relative to non-relationship venture debt, accounting for 23% (= 2.15/9.33) of the sample mean. Relationship-backed venture debt also increases the log amount raised in the follow-on VC round by 11 percentage points, compared to non-relationship venture debt. In net terms, the presence of a relationship offset 76% (=0.0215 / 0.0285) of the adverse effect on the likelihood of obtaining a follow-on VC round and 74% (=0.1096 / 0.1262) of the adverse impact on the log amount raised in the follow-on VC round. We also find a higher likelihood of obtaining a follow-on equity round with existing VCs, as shown in Column (6). Relationship-backed venture debt fully mitigates the adverse effect on the likelihood of obtaining a follow-on equity round with existing

VCs, accounting for 107% (= 0.0254 / 0.0237). These results suggest that relationships essentially undo the short-run dampening of equity fundraising associated with taking on venture debt, consistent with the information channel as in Hypothesis 4a.

6.3. Startup Exits

Next, we present results on startup exits over the three years following the venture debt deal, including IPOs, mergers, and bankruptcies. Table 10 reports the results.

Columns (1) and (2) focus on the likelihood of exiting through IPO. On average, venture debt startups are more likely to go public than their matched controls, with a coefficient of 16 basis points. This magnitude is economically significant, relative to the sample mean of 18 basis points. Moreover, when we add the relationship interaction term, we find the effects are primarily driven by relationship-backed venture debt, with a coefficient of 21 basis points. Put differently, the relationship-backed startups are 21 basis points more likely to go public than non-relationship venture debt startups, accounting for 117% (= 0.0021 / 0.0018) of the sample mean.

We find a similar pattern for the likelihood of exiting through M&A in Columns (3) and (4). The baseline difference-in-difference effect is significantly positive, with a coefficient of 31 basis points. When we add the relationship interaction term, the baseline terms shrink towards zero, and the interaction term remains strongly positive. Quantitatively, the relationship-backed venture debt startups are 44 basis points more likely to exit through M&A for non-relationship venture debt startups, accounting for 62% (= 0.0044 / 0.0071) of the sample mean.

[Insert Table 10 Here.]

Next, we turn to the likelihood of bankruptcy. In Column (5), we find that the average venture debt effect is almost zero, which acts as supportive evidence for the balanced matched sample. When we add the relationship interaction term, the coefficient remains statistically indistinguishable from zero. This suggests that venture debt, whether with or without a relationship, does not affect the failure risk in the near term..

Putting together the results, the results suggest that venture debt does improve the startup exit outcomes through IPO and M&A, and the results are primarily driven by relationship-backed venture debt. Meanwhile, venture debt does not affect startup failure. These patterns are most consistent with the information channel in Hypothesis 4a, where relationships ease verification and help connected borrowers reach value-creating exits.

6.4. Innovation Strategy

We next ask whether relationships shape the type of innovation firms pursue after receiving venture debt. Innovation outcomes matter for subsequent capital formation and value-creating exits, especially for young, VC-backed firms that account for a disproportionate share of novel technologies (Kortum and Lerner, 2000; Samila and Sorenson, 2011; Akcigit and Kerr, 2018). We implement the difference-in-differences specification described above on the matched sample and restrict the sample to startups observed throughout the event window, so that startups' exits do not attenuate the effects.

We begin by examining the aggregate innovation activities. We first look at the effects of receiving venture debt on the innovation intensity, as shown in Columns (1) and (3). We find that after receiving venture debt, the startups produce 0.3% fewer patents (t-statistic = -1.2) and 0.7% fewer citation-weighted patents (t-statistic = -1.8). The coefficients are marginally insignificant. If we move to the triple difference specification in Columns (2) and (4), we find that relationship-backed venture debt significantly increases the innovation intensity. Relative to non-relationship venture debt, the relationship-backed venture debt increases the number of patents by 0.85 percentage points, equivalent to 10% (= 0.0085/0.0848) of the average patenting intensity in our sample. For innovation quality, the corresponding coefficient for citation-weighted patents is 1.53 percentage points, or about 12% (= 0.0153/0.127) of the sample mean. In both cases, the relationship term largely offsets the small adverse baseline effect of taking on venture debt without a relationship, leaving aggregate innovation flat to slightly higher for connected borrowers.

[Insert Table 11 Here.]

The composition of innovation shifts toward outputs that are closer to commercialization. Columns (5) and (6) separate the patent portfolio into product and process innovation. We find that the startups with relationship-backed venture debt produce more product patents, with a significant coefficient of 0.81 percentage points, or about 13% (= 0.0081/0.0643) of the sample mean. In contrast, the effect on process patents is negligible and not statistically different from zero. This pattern is consistent with the idea that product innovation, as one of the key milestones for a startup, reduces uncertainty and helps open the door to the next financing round or a strategic exit (Gonzalez-Uribe and Mann, 2024).

To further explore how startups pursue different innovation strategies, we examine the innovation activities that vary by risk status. To do so, we leverage the richness of patent data by focusing on different patent characteristics, explorative vs. exploitative innovation (Almeida, Hsu and Li, 2013) in Columns (7) and (8), and high versus low breakthrough innovation (Kelly et al., 2021) in Columns (9) and (10). Across all dimensions, we find consistent patterns: relationship-backed venture debt significantly increases their engagement in safer and less resource-intensive innovation activities. For example, the coefficient for low explorative patents is 1.21 percentage points, while the estimate for high explorative patents is near zero. A similar pattern holds for breakthrough intensity. The relationship-backed venture debt increases the number of low-breakthrough patents by 1.21 percentage points, or about 23% (= 0.0121/0.0535) of the sample mean. In contrast, the coefficient on high-breakthrough patents is much smaller and not statistically different from zero. Together, the evidence points to an increase in market-facing and firm-specific projects that are less resource-intensive and easier to verify, rather than a shift toward radical or widely transferable innovations.

Putting all together, relationships do not simply scale innovation as the information channel of Hypothesis 4a. Instead, they reallocate post-deal effort toward product-oriented and comparatively safer lines that deliver earlier information to outside investors and facilitate follow-on financing and value-creating exits.

7. Conclusion Remarks

In this paper, we provide a theoretical framework and empirical evidence on how relationships between venture lenders and venture capital investors affect a venture debt deal across different stages. Unlike traditional relationship lending, where ties form directly between lenders and borrowers, venture debt relationships operate through the VC investors. Our theoretical framework highlights two competing channels: an information channel, where VC certification reduces asymmetric information and relaxes contracting frictions, and a market power channel, where repeated interactions allow lenders to extract rents from startups.

Using a comprehensive global dataset of venture debt contracts linked to startup characteristics, we document how these channels operate across the deal life cycle. At entry, VC–lender relationships expand the set of firms that can access debt, particularly those with high information asymmetry. During the investment stage, relationships substitute for hard contractual restrictions, easing monitoring intensity and collateral demands, while simultaneously allowing lenders to charge higher spreads. Post-deal, relationship-backed startups outperform: they are more likely to raise follow-on venture funding, achieve value-creating exits, and strategically reallocate innovative effort toward commercially salient and verifiable projects.

Taken together, our findings reveal the dual role of relationships in venture debt, which benefits both lenders and startups. Relationships reduce information frictions and support the growth of young, innovative firms, but they also strengthen lenders' bargaining position and enable rent extraction. Our results have important policy and practical implications. We highlight the distinctive nature of relationship lending in venture debt markets and underscore the importance of monitoring the systemic risks from concentrated repeated interactions, while recognizing their role in financing innovation. For practitioners, our findings highlight the strategic value of cultivating strong VC–lender ties.

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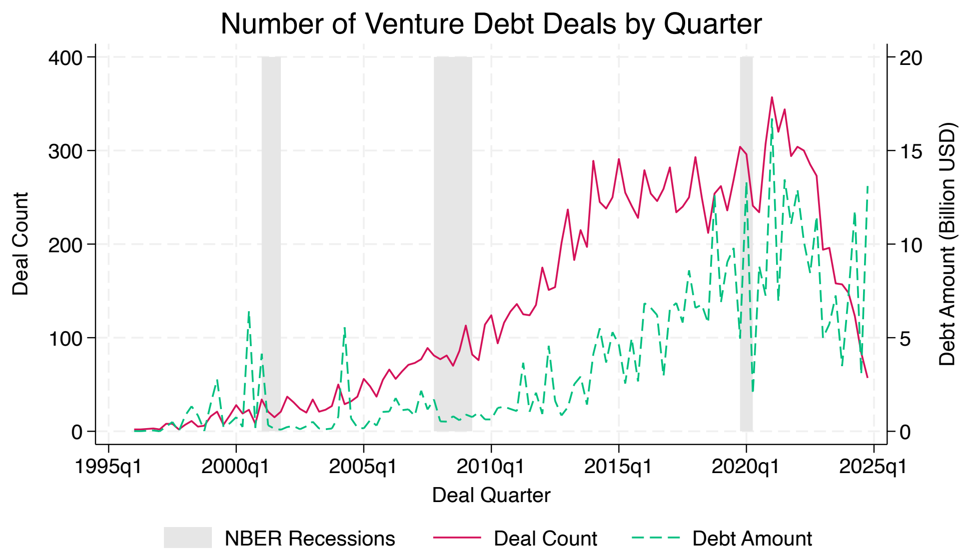
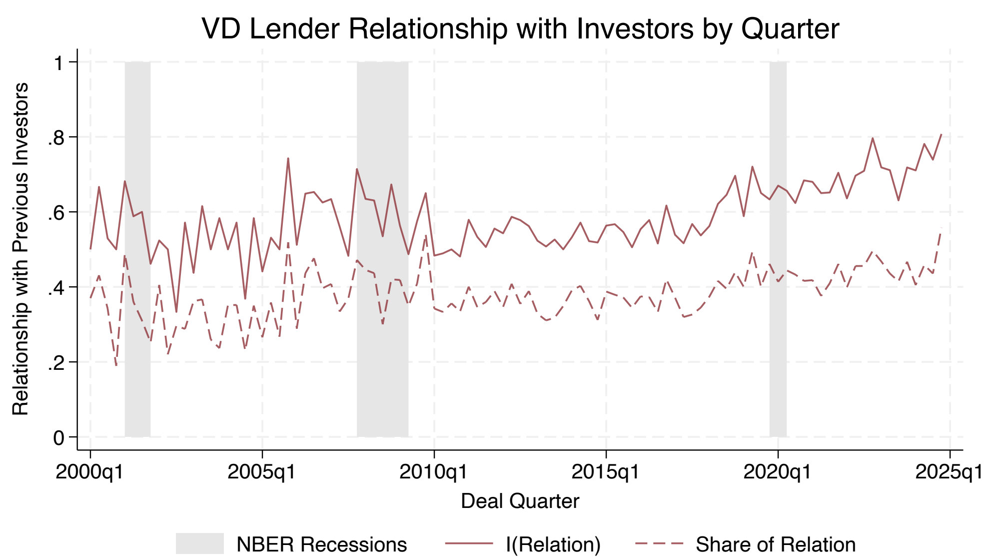
Figure 1. Venture Debt and Relationship By Time

Panel (a): Venture Debt Activity



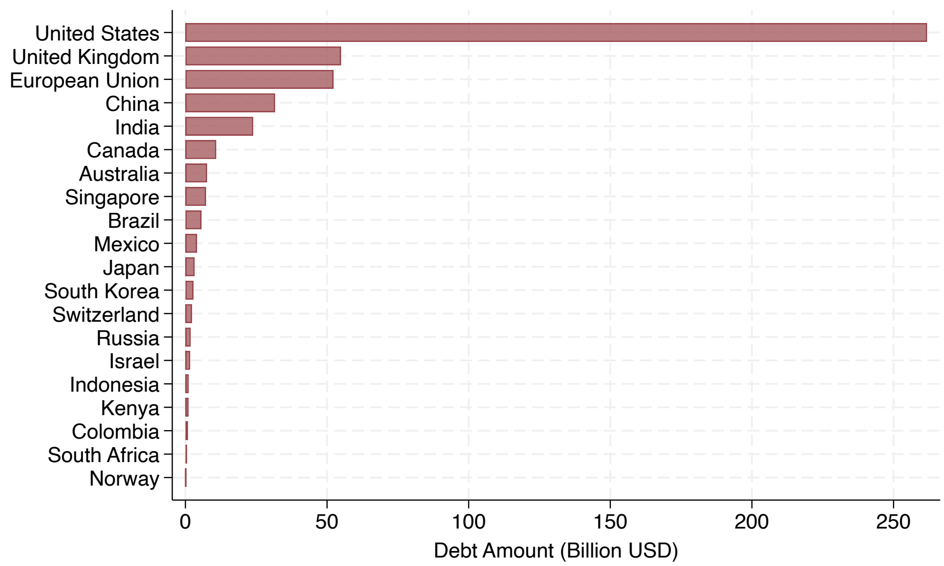
Panel (b): Venture Debt Relationship



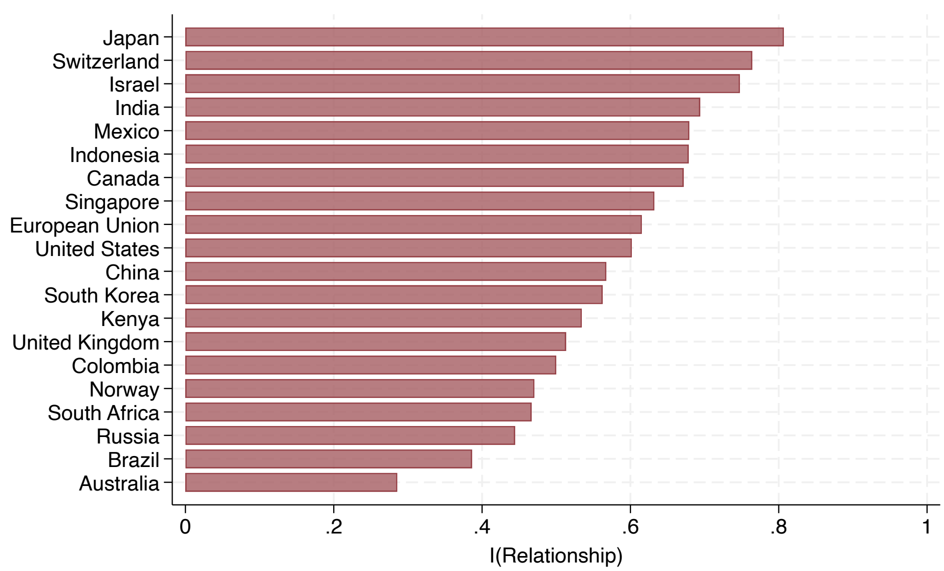
Notes. This figure plots the venture debt activity and average lender relationship by time. Panel (a) shows the number of venture debt deals by quarter (left axis) and the aggregate debt amount in millions of USD (right axis). Panel (b) reports the average strength of lender relationships with previous investors, measured as an indicator variable of whether at least one lender has been involved with the startup's VC investors and the average share of related investors among all past investors. The NBER-dated recessions are shaded.

Figure 2. Venture Debt by Country

Panel (a): Venture Debt Activity



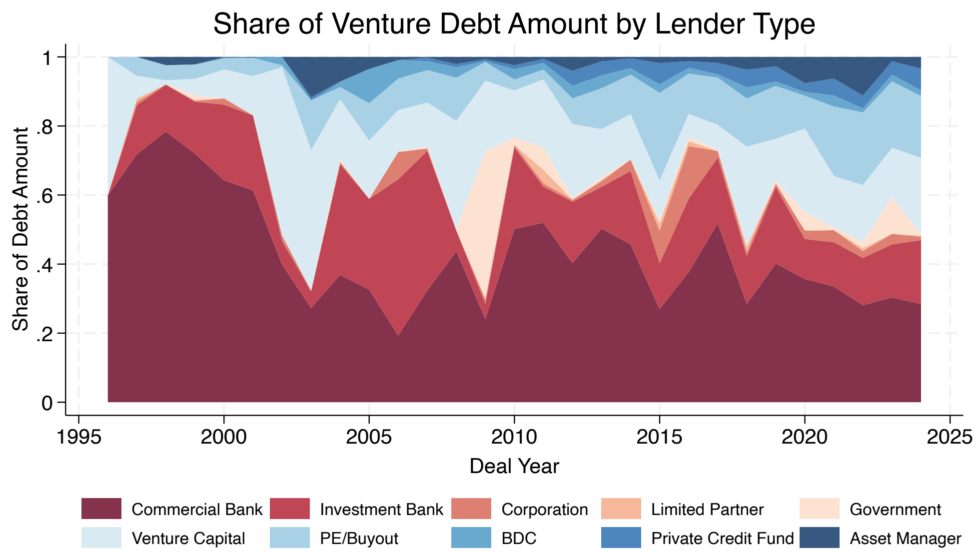
Panel (b): Venture Debt Relationship



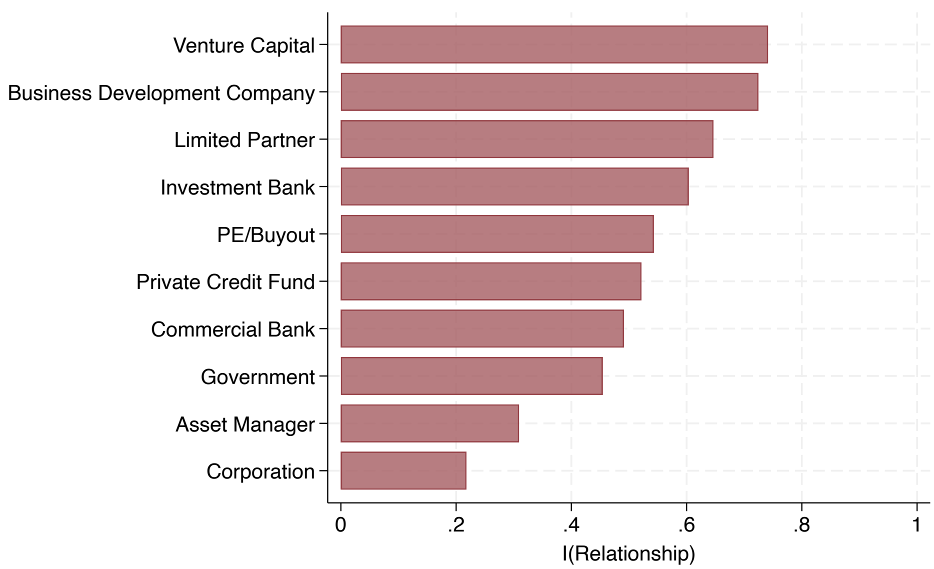
Notes. This figure presents venture debt activity and lender relationships by country. Panel (a) plots the aggregate venture debt amount in millions of USD by country over the sample period. Panel (b) reports the average venture debt relationship by country.

Figure 3. Venture Debt by Lender Type

Panel (a): Venture Debt Activity



Panel (b): Venture Debt Relationship



Notes. This figure presents venture debt activity and lender relationships by lender type. Panel (a) shows the time series of the share of total venture debt amount accounted for by different types of lenders between 1996 and 2024, including commercial banks, investment banks, corporations, limited partners, governments, venture capital, private equity/buyout funds, business development companies (BDCs), private credit funds, and asset managers. Panel (b) reports the venture debt relationship by lender type.

Table 1. Summary Statistics on Venture Debt

	count	mean	sd	min	p25	p50	p75	max
Panel (a): Deal Level Characteristics								
I(Relationship)	10,967	0.606	0.489	0	0	1	1	1
Share of Relation Investors	10,967	0.395	0.412	0	0	0.25	0.875	1
# Deal Round	15,451	4.592	3.245	1	2	4	6	36
Deal Size	12,140	40.272	201.928	0	0.99	4.907	20	7,500
Levered Financing	15,451	0.269	0.443	0	0	0	1	1
# Lenders	15,451	1.046	1.075	0	1	1	1	38
# Facility	12,883	1.123	0.442	1	1	1	1	10
Panel (b): Deal-Facility Level Characteristics								
I(Relationship)	12,418	0.602	0.490	0	0	1	1	1
Share of Relation Investors	12,418	0.391	0.411	0	0	0.25	0.857	1
Spread	1,947	763.250	350.127	1	500	750	1,050	2,399
Debt Amount	9,610	41.363	429.384	0	0.783	4	15	37,795.49
Maturity	3,960	4.773	3.663	0	3.003	4.616	5.003	31.899
Term Loan	14,462	0.856	0.351	0	1	1	1	1
Revolving Credit	14,462	0.077	0.267	0	0	0	0	1
Senior	12,408	0.189	0.391	0	0	0	0	1
Secured	12,408	0.228	0.419	0	0	0	0	1
1st Lien	12,408	0.030	0.169	0	0	0	0	1
Cov-lite	12,408	0.003	0.052	0	0	0	0	1
Convertible	12,408	0.018	0.133	0	0	0	0	1
Panel (c): Company Characteristics								
Employment	14,004	156.056	1,145.697	0	9	32	95	65,193
Cum. Fin Amount	15,451	112.600	673.472	0	1.66	13	57.858	24,941.50
Age	15,451	26.166	17.537	0	13	23	36	80
# Trademark	15,039	2.140	4.752	0	0	0	3	124
Revenue / Employees	3,588	2.746	44.400	0	0.046	0.135	0.33	1,639.949
EBITDA / Employees	1,310	-0.207	2.622	-45.4	-0.164	-0.049	0.004	18.744
Net Income / Employees	2,021	-0.324	3.849	-84.371	-0.164	-0.047	-0.004	69.805
I(Same City as Lender)	12,331	0.111	0.306	0	0	0	0	1
Distance to Lender	12,329	2,086.214	2,854.213	0	59.781	910.335	3,391.74	17,741.79

Notes. This table presents summary statistics. Panel (a) presents deal-level characteristics. I(Relationship) is an indicator variable of whether at least one lender has been involved with the startup's VC investors. Share of Relation Investors is the share of related investors among all past investors. # Deal Round is the number of financing rounds for the debt deal. Deal Size is the total facility amount at issuance. Levered Financing is an indicator of whether the venture debt is a levered financing deal. # Lenders and # Facility report the number of lenders and the number of facilities within each deal. Panel (b) reports deal-facility level characteristics. Spread is the reported loan spread in basis points. Debt Amount is the dollar amount of the facility. Maturity is the facility's maturity in years. Term Loan and Revolving Credit are indicators for term loan and revolving credit, respectively. Senior, Secured, and 1st Lien are indicators for senior, collateral, and 1st lien facilities, respectively. Cov-lite indicates covenant-lite facilities. Convertible indicates loans with conversion rights. Panel (c) reports company-level characteristics measured at the time of the deal. Employment is the number of employees. Cum. Fin Amount is the total venture financing raised by the startup (in million USD). Age is the number of quarters since founding. # Trademarks is the total count of registered trademarks. Revenue, EBITDA, and Net Income are scaled by the number of employees. I(Same City as Lender) is an indicator equal to one if the lender and borrower are headquartered in the same city. Distance to Lender is the geographic distance between borrower and lender headquarters, measured in kilometers.

Table 2. Venture Debt Relationship by Industry

Industry	I(Relationship)	Share of Relation	Deal Count	Debt Amount (MM USD)
Panel (a): Top Industries (Highest Relationship)				
Materials and Resources - Chemicals and Gases	0.789	0.528	89	5,542.95
Financial Services - Insurance	0.735	0.425	56	1,090.81
Information Technology - Semiconductors	0.707	0.480	162	1,074.22
Information Technology - Computer Hardware	0.706	0.481	313	5,502.68
Energy - Utilities	0.679	0.434	59	1,986.48
Consumer Products and Services (B2C) - Retail	0.673	0.429	258	3,202.63
Healthcare - Healthcare Devices and Supplies	0.673	0.434	815	7,016.06
Information Technology - Communications and Networking	0.659	0.460	400	25,956.61
Information Technology - Software	0.647	0.412	3,575	80,301.06
Healthcare - Pharmaceuticals and Biotechnology	0.637	0.432	830	10,378.98
Panel (b): Bottom Industries (Lowest Relationship)				
Energy - Energy Services	0.500	0.283	115	5,739.96
Consumer Products and Services (B2C) - Restaurants, Hotels and Leisure	0.490	0.330	255	11,293.50
Financial Services - Capital Markets/Institutions	0.490	0.297	56	7,641.88
Materials and Resources - Agriculture	0.451	0.294	122	1,503.22
Materials and Resources - Containers and Packaging	0.419	0.273	39	1,572.23
Energy - Exploration, Production and Refining	0.411	0.280	78	3,656.76
Consumer Products and Services (B2C) - Consumer Non-Durables	0.405	0.272	599	7,730.16
Materials and Resources - Metals, Minerals and Mining	0.368	0.213	21	4,697.92

Notes. This table reports the average deal-level relationship by PitchBook industry sector and groups. Panel (a) lists the top ten industries with the highest average relationships, and Panel (b) lists the bottom ten industries with the lowest average relationships. I(Relationship) is an indicator variable of whether at least one lender has been involved with the startup's VC investors. Share of Relation Investors is the share of related investors among all past investors. Deal count and debt amount are the number of deals and the total deal amount in our sample.

Table 3. Venture Debt Relationship and Ex-ante Asymmetric Info

	(1)	(2)	(3)	(4)	(5)
$Y_{d,l,i}$ =	I(Venture Debt Deal)				
I(Relationship)$_{d,l,i}$ x AsymInfo$_{d,i}$	0.009***	0.021***	0.009***	0.009***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
I(Relationship)$_{d,l,i}$	0.240***	0.230***	0.240***	0.261***	0.216***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.012)
ln(Cum. Patent)$_{d,i}$	-0.002***				
	(0.000)				
ln(Cum. Citation)$_{d,i}$		-0.003***			
		(0.000)			
ln(Cum. CW Patent)$_{d,i}$			-0.002***		
			(0.000)		
-ln(Cum. News)$_{d,i}$				-0.001**	
				(0.000)	
ln(1+Distance)$_{d,i}$					-0.005***
					(0.000)
I(Relationship)$_{d,l,i}$ x Same City$_{d,i}$					0.133***
					(0.020)
I(Same City)$_{d,i}$					-0.004**
					(0.002)
$\beta_1 + \beta_2$	0.0065**	0.0182***	0.0066***	0.0077**	0.0025
Observations	522,585	522,585	522,585	522,585	486,395
Adj. R^2	0.25	0.25	0.25	0.25	0.25
DealxLender FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean DV	0.017	0.017	0.017	0.017	0.017

Notes. This table examines the effect of the venture debt relationship on the likelihood of obtaining venture debt under different measures of ex-ante asymmetric information using a matched sample. The dependent variable is an indicator equal to one if startup i receives venture debt in deal d from lender l. I(Relationship)$_{d,l,i}$ is an indicator variable of whether the lender is involved with the startup's VC investors. Asymmetric information is proxied by cumulative patents in Column (1), cumulative citations in Column (2), cumulative citation-weighted patents in Column (3), negative value of cumulative news coverage in Column (4), and geographic distance between the lender and startup headquarters in Column (5). We control for the log number of employment, the log value of cumulative financing amount, and the log value of age. In Column (5), we also control for an indicator equal to one if the lender and borrower are headquartered in the same city, and its interaction terms with the relationship measure. Interaction terms test whether relationships mitigate the negative effect of information frictions, i.e., $H_0 : \beta_1 + \beta_2 = 0$. The model includes deal-lender fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Venture Debt Relationship and Ex-ante Industry R&D Intensity

	(1)	(2)	(3)	(4)
$Y_{d,l,i}$ =	I(Venture Debt Deal)			
I(Relationship)$_{d,l,i}$ x R&D/Asset (Mean)$_{ind}$	0.108***			
	(0.005)			
I(Relationship)$_{d,l,i}$ x R&D/Asset (Med.)$_{ind}$		0.078***		
		(0.005)		
I(Relationship)$_{d,l,i}$ x R&D/Sales (Mean)$_{ind}$			0.032***	
			(0.004)	
I(Relationship)$_{d,l,i}$ x R&D/Sales (Med.)$_{ind}$				0.038***
				(0.005)
I(Relationship)$_{d,l,i}$	0.164***	0.181***	0.227***	0.237***
	(0.006)	(0.007)	(0.006)	(0.005)
Observations	522,585	522,585	522,585	522,585
Adj. R^2	0.26	0.26	0.25	0.25
DealxLender FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean DV	0.017	0.017	0.017	0.017

Notes. This table examines the effect of the venture debt relationship on the likelihood of obtaining venture debt across industries with different levels of R&D intensity. The dependent variable is an indicator equal to one if startup i receives venture debt in deal d from lender l. I(Relationship)$_{d,l,i}$ is an indicator variable of whether the lender is involved with the startup's VC investors. Industry R&D intensity is measured using the publicly traded firms from Compustat in the same quarter. Columns (1)–(2) use R&D-to-assets, calculated as the industry mean and median. Columns (3)–(4) use R&D-to-sales at the mean and median. We control for the log number of employment, the log value of cumulative financing amount, and the log value of age. The model includes deal-lender fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Venture Debt Relationship and Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{d,i}$ =	ln(Revenue)	Net Income Margin	EBITDA Margin	Revenue/Emp	ln(Cum. Trademark)	ln(Cum. Patent)
I(Relationship)$_d$	-0.061	1.692	0.485	-0.002	-0.028	0.031
	(0.064)	(4.447)	(3.352)	(0.136)	(0.019)	(0.021)
ln(Employment)$_{d,i}$	0.434***	-2.104	-0.117	-1.246***	0.104***	0.020*
	(0.041)	(2.576)	(0.945)	(0.215)	(0.009)	(0.012)
ln(Cum. Fin Amount)$_{d,i}$	0.320***	-0.026	-0.671	0.701***	0.094***	0.151***
	(0.034)	(1.605)	(0.715)	(0.130)	(0.009)	(0.011)
ln(Age)$_{d,i}$	0.295***	11.070**	4.673	0.280	0.226***	0.211***
	(0.068)	(4.856)	(3.236)	(0.175)	(0.014)	(0.017)
1(Same City as Lender)$_{d,i}$	-0.033	4.518	-5.047	0.471	0.067	-0.132***
	(0.157)	(12.421)	(8.745)	(0.326)	(0.042)	(0.050)
ln(Distance to Lender)$_{d,i}$	0.011	1.178	-0.438	0.110**	0.015***	-0.009
	(0.018)	(1.621)	(1.035)	(0.043)	(0.005)	(0.006)
Observations	2,476	1,104	639	2,450	9,255	9,345
Adj. R^2	0.662	0.402	0.358	0.357	0.433	0.453
Deal Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	2.748	-9.926	-5.768	0.710	0.771	0.607

Notes. This table examines the relation between venture debt relationship and firm characteristics at the time of the deal. The dependent variables are log value of revenue in Column (1), net income margin (= net income / revenue) in Column (2), EBITDA margin (= EBITDA / revenue) in Column (3), revenue per employee in Column (4), log number of trademarks in Column (5), and log number of patents in Column (6). I(Relationship)$_d$ is an indicator variable of whether the lender is involved with the startup's VC investors. We control for the log number of employment, the log value of cumulative financing amount, the log value of age, an indicator for whether the lender and borrower are headquartered in the same city, and the log geographic distance between lender and borrower headquarters. The model includes deal round fixed effects, industry-year fixed effects, and country-year fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Venture Debt Relationship and Loan Contract Terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Y_{d,i}$ =	Term Loan		Revolving Credit		Secured		1st Lien	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
I(Relationship)$_d$	-0.030***	-0.048*	0.011*	0.019	-0.100***	-0.131***	-0.009*	-0.059***
	(0.008)	(0.027)	(0.006)	(0.019)	(0.012)	(0.035)	(0.005)	(0.014)
ln(Employment)$_{d,i}$	-0.019***	-0.019***	0.022***	0.022***	0.002	0.000	0.010***	0.010***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)
ln(Cum. Fin Amount)$_{d,i}$	-0.015***	-0.014***	0.010***	0.010***	-0.025***	-0.020***	0.005*	0.008***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.003)
ln(Age)$_{d,i}$	0.001	0.002	-0.002	-0.005	0.029***	0.028***	0.007*	0.004
	(0.006)	(0.006)	(0.005)	(0.005)	(0.009)	(0.010)	(0.004)	(0.004)
1(Same City as Lender)$_{d,i}$	-0.041**	-0.044**	-0.004	-0.004	0.029	0.018	0.023**	0.014
	(0.020)	(0.020)	(0.014)	(0.014)	(0.025)	(0.026)	(0.010)	(0.009)
ln(Distance to Lender)$_{d,i}$	-0.006***	-0.006***	0.004**	0.004**	0.008***	0.006**	0.003***	0.002**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	10,637	10,205	10,637	10,205	9,210	8,821	9,210	8,821
R-squared	0.133	0.014	0.136	0.019	0.270	0.021	0.162	-0.001
Deal-Facility Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.847	0.845	0.0882	0.0876	0.231	0.222	0.0338	0.0333
First-Stage Coefficients and F-Statistic								
VCs' Lender HHI		-0.554***		-0.554***		-0.555***		-0.555***
		(0.019)		(0.019)		(0.020)		(0.020)
F-Statistic		882.9		882.9		747.9		747.9

Notes. This table examines the effect of venture debt relationships on loan contract terms at the facility level. The dependent variables are an indicator for term loan in Columns (1)-(2), an indicator for revolving credit in Columns (3)-(4), an indicator for secured in Columns (5)-(6), and an indicator for first lien in Columns (7)-(8). I(Relationship)$_d$ is an indicator variable of whether the lender is involved with the startup's VC investors. We control for the log number of employment, the log value of cumulative financing amount, the log value of age, an indicator for whether the lender and borrower are headquartered in the same city, and the log geographic distance between lender and borrower headquarters. For each outcome, we report the results using both OLS and IV regressions, as described in Section 5.1. We report the first-stage coefficients and F-statistics for the instrumental variable regressions in the bottom of the table. The model includes deal-facility-round fixed effects, industry-year fixed effects, and country-year fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Venture Debt Relationship and Loan Spread

	(1)	(2)	(3)	(4)	(5)
$Y_{d,i}$ =	Spread				
	OLS	OLS	OLS	OLS	IV
I(Relationship)$_d$	84.631***	141.954***	110.254***	87.705***	196.271***
	(29.454)	(30.468)	(26.779)	(31.033)	(70.149)
ln(Employment)$_{d,i}$		-27.994***	-24.938***	-39.621***	-48.693***
		(9.764)	(8.934)	(12.207)	(13.205)
ln(Cum. Fin Amount)$_{d,i}$		-20.864**	-18.350**	-21.216**	-26.534**
		(8.361)	(7.528)	(9.795)	(11.132)
ln(Age)$_{d,i}$		7.560	8.358	-47.270**	-23.523
		(19.223)	(17.705)	(18.500)	(20.422)
1(Same City as Lender)$_{d,i}$		-189.270**	-75.441	18.697	23.959
		(77.358)	(80.529)	(87.453)	(94.314)
ln(Distance to Lender)$_{d,i}$		-11.362*	-5.379	-2.777	-1.318
		(6.139)	(5.380)	(6.102)	(6.251)
I(Term Loan)$_{d,i}$			102.502	140.074*	149.587*
			(69.099)	(78.574)	(79.905)
I(Revolving Credit)$_{d,i}$			-201.851***	-42.332	-28.454
			(72.533)	(84.300)	(86.297)
I(Secured)$_{d,i}$			185.437***	237.960***	235.872***
			(22.072)	(23.002)	(24.182)
Observations	1,687	1,600	1,600	1,424	1,336
R-squared	0.011	0.065	0.197	0.552	0.193
Deal-Facility Round FE	No	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes	Yes
Country-Year FE	No	No	No	Yes	Yes
Mean DV	784.6	783	783	781.8	802.6
First-Stage Coefficients and F-Statistic					
VCs' Lender HHI					-0.731***
					(0.060)
F-Statistic					150.3

Notes. This table examines the effect of venture debt relationships on loan spread at the facility level. The dependent variable is the loan spread. I(Relationship)$_d$ is an indicator variable of whether the lender is involved with the startup's VC investors. We control for the log number of employment, the log value of cumulative financing amount, the log value of age, an indicator of whether the lender and borrower are headquartered in the same city, and the log geographic distance between lender and borrower headquarters in Columns (2)-(5). We further control for loan characteristics, including the indicators of whether the loan is a term loan, revolving credit, and secured in Columns (3)-(5). We use OLS specifications in Columns (1)-(4) and IV specifications in Column (5), as described in Section 5.1. We report the first-stage coefficients and F-statistics for the instrumental variable regressions in the bottom of the table. The model includes deal-facility-round fixed effects, industry-year fixed effects and country-year fixed effects in Columns (4)-(5). Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Loan Price, Outside Options, and Agency Conflict

Panel (a): Loan Price Outside Options

	(1)	(2)	(3)
$Y_{d,i}$ =		Spread	
Measure of Outside Options	# VCs' Lenders	VC Has Lending Business	# Local Lenders
I(Relationship)$_{d,i}$ x LowOutsideOptions$_{d,i}$	129.452**	128.743**	137.921***
	(56.635)	(56.813)	(52.290)
I(Relationship)$_d$	-7.769	-2.523	53.333
	(42.923)	(40.527)	(34.609)
LowOutsideOptions$_{d,i}$	-95.868*	-80.475	-117.540**
	(52.401)	(50.328)	(48.017)
Observations	1,336	1,336	1,424
R-squared	0.542	0.543	0.555
Deal-Facility Round FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Firm Controls and Loan Characteristics Controls	Yes	Yes	Yes
Mean DV	802.6	802.6	781.8

Panel (b): Loan Price and Agency Conflict

	(1)	(2)	(3)
$Y_{d,i}$ =		Spread	
Measure of VC Control/Pressue	# VCs	VCs' Age	VCs' Portfolio Size
I(Relationship)$_{d,i}$ x HighVCPressue$_{d,i}$	143.595**	121.525**	134.734**
	(66.320)	(59.556)	(59.393)
I(Relationship)$_d$	42.713	48.199	41.400
	(33.287)	(33.063)	(34.199)
HighVCPressue$_{d,i}$	-134.942**	-153.619***	-150.744***
	(63.771)	(56.247)	(55.406)
Observations	1,336	1,336	1,336
R-squared	0.541	0.542	0.542
Deal-Facility Round FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Firm Controls and Loan Characteristics Controls	Yes	Yes	Yes
Mean DV	802.6	802.6	802.6

Notes. This table examines the effect of venture debt relationships on loan spread at the facility level, by startup heterogeneity in terms of outside options and VC agency conflicts. In Panel (a), we interact the relationship indicator with various dummy variables for which startups have the outside options below bottom 30th percentile level. We use three proxies for low outside options, including the number of lenders that the VCs have worked with, whether the VC has no lending business, and the number of local lenders in the same country and industry. In Panel (b), we interact the relationship indicator with various dummy variables for which startups have the VC agency conflicts above top 30th percentile level. We use three proxies for VC agency conflicts, including the number of startup's VC investors, the VC's age, and the VC's portfolio size. I(Relationship)$_d$ is an indicator variable of whether the lender is involved with the startup's VC investors. We control for the log number of employment, the log value of cumulative financing amount, the log value of age, an indicator of whether the lender and borrower are headquartered in the same city, and the log geographic distance between lender and borrower headquarters. We also control for loan characteristics, including the indicators of whether the loan is a term loan, revolving credit, and secured. The models include deal-facility-round fixed effects, industry-year fixed effects and country-year fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Venture Debt Relationship and Future Financing Rounds

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{d,i,t}$ =	1(VC Deals)		ln(VC Deal Amount)		1(VC Deals w/ Previous VCs)	
Treated$_{d,i}$ x Post$_{d,t}$ x I(Relationship)$_d$		0.0215***		0.1096***		0.0254***
		(0.0044)		(0.0107)		(0.0028)
Treated$_{d,i}$ x Post$_{d,t}$	-0.0155***	-0.0285***	-0.0597***	-0.1262***	-0.0082***	-0.0237***
	(0.0023)	(0.0034)	(0.0059)	(0.0078)	(0.0015)	(0.0020)
ln(Employment)$_{d,t}$	-0.0257***	-0.0257***	-0.0733***	-0.0733***	-0.0112***	-0.0112***
	(0.0014)	(0.0014)	(0.0034)	(0.0034)	(0.0009)	(0.0009)
ln(Cum. Fin Amount)$_{d,t}$	0.1405***	0.1406***	0.4017***	0.4026***	0.0775***	0.0777***
	(0.0017)	(0.0017)	(0.0047)	(0.0047)	(0.0012)	(0.0012)
ln(Age)$_{d,t}$	-0.1751***	-0.1762***	-0.3801***	-0.3859***	-0.0520***	-0.0534***
	(0.0100)	(0.0100)	(0.0211)	(0.0211)	(0.0058)	(0.0058)
Observations	970,946	970,946	970,946	970,946	970,946	970,946
Adj. R^2	0.2513	0.2513	0.2822	0.2823	0.2442	0.2443
Event-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event-Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.0933	0.0933	0.174	0.174	0.0415	0.0415

Notes. This table examines the effect of venture debt relationships on startups' subsequent financing outcomes using a stacked triple-difference specification with the matched sample. We consider a five-year window around the deal quarter, with a two-year pre-event window and a three-year post-event window. We require the startup to be observed for at least two years before the deal in the pre-event window. The dependent variables are an indicator for obtaining a follow-on VC deal in quarter t in Columns (1)-(2), the log amount of VC financing raised in Columns (3)-(4), and an indicator for obtaining a follow-on VC deal with previous VCs in Columns (5)-(6). I(Relationship)$_d$ is an indicator variable of whether the lender has been involved with the startup's VC investors, which is defined at origination and held fixed across startups and time within the same event-matched group. Treated$_{d,i}$ equals one for the treated startup in venture debt deal d and zero for its matched control groups. Post$_{d,t}$ equals one for quarters in the three-year post-event window $[t, t+12]$. We control for the log number of employment, the log value of cumulative financing amount, and the log value of age. The model includes event-firm fixed effects and event-date fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Venture Debt Relationship, Exit and Bankruptcy

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{d,i,t}$ =	1(IPO)		1(Merger & Acquisition)		1(Bankruptcy)	
Treated$_{d,i}$ x Post$_{d,t}$ x I(Relationship)$_d$		0.0021***		0.0044***		0.0001
		(0.0005)		(0.0012)		(0.0004)
Treated$_{d,i}$ x Post$_{d,t}$	0.0016***	0.0003	0.0031***	0.0004	0.0002	0.0001
	(0.0003)	(0.0003)	(0.0007)	(0.0009)	(0.0002)	(0.0003)
ln(Employment)$_{d,i,t}$	0.0003	0.0003	-0.0297***	-0.0297***	-0.0049***	-0.0049***
	(0.0002)	(0.0002)	(0.0009)	(0.0009)	(0.0003)	(0.0003)
ln(Cum. Fin Amount)$_{d,i,t}$	0.0016***	0.0016***	0.0030***	0.0031***	0.0007***	0.0007***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
ln(Age)$_{d,i,t}$	0.0004	0.0003	0.0115***	0.0113***	0.0040***	0.0040***
	(0.0010)	(0.0010)	(0.0027)	(0.0027)	(0.0010)	(0.0010)
Observations	970,946	970,946	970,946	970,946	970,946	970,946
Adj. R^2	0.2017	0.2017	0.2207	0.2208	0.2204	0.2204
Event-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Event-Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.00181	0.00181	0.00711	0.00711	0.000761	0.000761

Notes. This table examines the effect of venture debt relationships on startups' future exit and bankruptcy outcomes using a stacked triple-difference specification with the matched sample. We consider a five-year window around the deal quarter, with two year pre-event window and three-year post-event window. We require the startup to be observed for at least two years before the deal in the pre-event window. The dependent variables are an indicator of whether the startup i in quarter t goes to IPO in Columns (1)-(2), whether it is acquired in Columns (3)-(4), or whether it files for bankruptcy in Columns (5)-(6). I(Relationship)$_d$ is an indicator variable of whether the lender has been involved with the startup's VC investors, which is defined at origination and held fixed across startups and time within the same event-matched group. Treated$_{d,i}$ equals one for the treated startup in venture debt deal d and zero for its matched control groups. Post$_{d,t}$ equals one for quarters in the three-year post-event window $[t, t+12]$. We control for the log number of employment, the log value of cumulative financing amount, and the log value of age. The model includes event-firm fixed effects and event-date fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Venture Debt Relationship and Future Innovation Activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Y_{d,i,t}$ =	ln(Patent)		ln(CW Patent)		ln(Product/Process Patent)		ln(Explorative Patent)		ln(Breakthrough Patent)	
					Product	Process	Low	High	Low	High
Treated$_{d,i}$ x Post$_{d,t}$ x I(Relationship)$_d$		0.0085*		0.0153**	0.0081**	0.0034	0.0121***	-0.0006	0.0074**	0.0039
		(0.0045)		(0.0072)	(0.0039)	(0.0026)	(0.0039)	(0.0028)	(0.0035)	(0.0041)
Treated$_{d,i}$ x Post$_{d,t}$	-0.0032	-0.0081***	-0.0074*	-0.0162***	-0.0062**	-0.0031**	-0.0084***	-0.0008	-0.0038	-0.0059**
	(0.0027)	(0.0029)	(0.0041)	(0.0050)	(0.0026)	(0.0015)	(0.0023)	(0.0018)	(0.0023)	(0.0025)
ln(Employment)$_{d,t}$	0.0273***	0.0273***	0.0349***	0.0349***	0.0200***	0.0099***	0.0159***	0.0110***	0.0127***	0.0210***
	(0.0018)	(0.0018)	(0.0029)	(0.0029)	(0.0016)	(0.0010)	(0.0014)	(0.0012)	(0.0012)	(0.0019)
ln(Cum. Fin Amount)$_{d,t}$	0.0055***	0.0056***	0.0098***	0.0099***	0.0048***	0.0010	0.0044***	0.0008	0.0026***	0.0044***
	(0.0012)	(0.0012)	(0.0019)	(0.0019)	(0.0011)	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0012)
ln(Age)$_{d,t}$	0.0224**	0.0219**	0.0290*	0.0282	0.0189*	0.0050	0.0139	0.0087	0.0148*	0.0090
	(0.0111)	(0.0111)	(0.0175)	(0.0175)	(0.0100)	(0.0054)	(0.0092)	(0.0067)	(0.0081)	(0.0105)
Observations	759,604	759,604	759,604	759,604	759,604	759,604	759,604	759,604	693,213	693,213
Adj. R^2	0.5848	0.5848	0.5628	0.5628	0.5595	0.4980	0.5720	0.4438	0.5364	0.5491
Event-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event-Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.0848	0.0848	0.127	0.127	0.0643	0.0269	0.0535	0.0306	0.0431	0.0529

Notes. This table examines the effect of venture debt relationships on startups' future innovation outcomes using a stacked triple-difference specification with the matched sample. We consider a five-year window around the deal quarter, with two year pre-event window and three-year post-event window. We require the startup to be observed throughout the entire event window. The dependent variables are the log number of patents in Column (1)-(2) and the log number of citation-weighted patents in Column (3)-(4). Columns (5)-(6) consider the log number of product versus process patents, measured by Bena and Simintzi (2023). Columns (7)-(8) consider the log number of explorative versus exploitative patents, measured by (Almeida, Hsu and Li, 2013). Columns (9)-(0) consider the log number of high versus low breakthrough patents, measured by (Kelly et al., 2021). I(Relationship)$_d$ is an indicator variable of whether the lender has been involved with the startup's VC investors, which is defined at origination and held fixed across startups and time within the same event-matched group. Treated$_{d,i}$ equals one for the treated startup in venture debt deal d and zero for its matched control groups. Post$_{d,t}$ equals one for quarters in the three-year post-event window $[t, t+12]$. We control for the log number of employment, the log value of cumulative financing amount, and the log value of age. The model includes event-firm fixed effects and event-date fixed effects. 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. Proofs

A.1.1. Proof of Lemma 1: Participation Constraint

The lender's participation requires $\Pi_l \geq 0$, which is equivalent to

$$r \geq r^{BE} \equiv \frac{L + c(m)}{s\,L} - 1, \tag{A1}$$

where r^{BE} is the break-even price of the lender.

The startup's participation requires $\Pi_i \geq 0$, which is equivalent to

$$r \leq r^{FC} \equiv \frac{X_S}{L} - 1, \tag{A2}$$

where r^{FC} is the feasibility cap of the startup.

Both parties can accept a price if and only if the interval $[r^{BE}, r^{FC}]$ is nonempty, that is,

$$r^{BE} \leq r^{FC} \quad \Longleftrightarrow \quad \Pi_{total} \geq 0. \tag{A3}$$

When $\Pi_{total}(L, m; R) < 0$, no price satisfies both constraints, and the deal is infeasible.

A.1.2. Proof of Lemma 2: Asymmetric Information and Access to Finance

Given (L, m), let's define the value of total surplus at belief p_l as $V(p_l; L, m) = \Pi_{total}(L, m; p_l) = s(p_l, m)X_s - L - c(m)$. The derivative of the value of total surplus $V(p_l; L, m)$ with respect to the belief p_l is given by

$$\frac{\partial V(p_l; L, m)}{\partial p_l} = (1 - \phi(m))X_s \geq 0, \tag{A4}$$

where the last inequality follows from the assumption that $\phi(m) \in [0, 1)$ and $X_s > 0$.

When $p_l = 0$, $s(p_l, m) = \phi(m)$, so $V(0; L, m) = \phi(m)X_s - L - c(m)$. The first order condition implies that $\phi'(\underline{m})X_s - c'(\underline{m}) = 0$, where $\underline{m}$ is the monitoring intensity that satisfies this first order condition. In this case, $V(0; L, m) = \phi(\underline{m})X_s - L - c(\underline{m}) < 0 \iff L > \phi(\underline{m})X_s - c(\underline{m})$.

When $p_l = 1$, $s(p_l, m) = 1$, so $V(1; L, m) = X_s - L - c(m)$. In this case, $V(1; L, m) = X_s - L - c(m) > X_s - L > 0 \iff L < X_s$.

Putting together, if $\phi(\underline{m})X_s - c(\underline{m}) < L < X_s$, then $V(0) < 0 < V(1)$. By the intermediate value theorem, there exists a unique belief $p_l^* = \frac{L+c(m)-\phi(m)X_s}{(1-\phi(m))X_s}$ such that lending occurs if and only if $p_l \geq p_l^*$.

A.1.3. Proof of Proposition 1: Access to Finance and Relationship

Lender's contracting belief $p_l(R) = p_{l,0} + \delta(p_{l,0}, \lambda)R$, which gives

$$\frac{\partial p_l(R)}{\partial R} = \delta(p_{l,0}, \lambda) \geq 0, \tag{A5}$$

where the last inequality follows from the assumption that $\delta(p_{l,0}, \lambda) \in [0, 1 - p_{l,0}]$.

Combining with Lemma (2), we have

$$\frac{\partial V(p_l(R); L, m)}{\partial R} = \frac{\partial V(p_l(R); L, m)}{\partial p_l} \frac{\partial p_l(R)}{\partial R} = (1 - \phi(m))X_s \delta(p_{l,0}, \lambda) \geq 0, \tag{A6}$$

where the equality holds when $\phi(m) = 1$.

Given $\delta(p_{l,0}, \lambda) = \frac{\lambda - 1}{\lambda \frac{p_{l,0}}{1-p_{l,0}} + 1}$, we have

$$\frac{\partial \delta(p_{l,0}, \lambda)}{\partial p_{l,0}} = -\frac{\lambda(\lambda - 1)}{(\lambda p_{l,0} + 1 - p_{l,0})^2} < 0, \tag{A7}$$

where the last inequality follows from the assumption that $\lambda > 1$. Therefore, the second derivative is given by

$$\frac{\partial^2 V(p_l(R); L, m)}{\partial p_{l,0} \partial R} = -(1 - \phi(m))X_s \frac{\lambda(\lambda - 1)}{(\lambda p_{l,0} + 1 - p_{l,0})^2} \leq 0, \tag{A8}$$

where the equality holds when $\phi(m) = 1$.

A.1.4. Proof of Lemma 3: Optimal Debt Spread

The solution of Nash bargaining problem is $\Pi_l = \theta(R)\Pi_{total}$. Solving for the optimal price r^*, we have

$$r^* = \underbrace{\left(\frac{L + c(m)}{s(p_l(R), m)L} - 1\right)}_{= \text{break-even price } r^{BE}} + \theta(R) \underbrace{\frac{\Pi_{total}}{s(p_l(R), m)L}}_{= \text{markup } \mu} \tag{A9}$$

$$= (1 - \theta(R)) \underbrace{\left(\frac{L + c(m)}{s(p_l(R), m)L} - 1\right)}_{= \text{break-even price } r^{BE}} + \theta(R) \underbrace{\left(\frac{X_S}{L} - 1\right)}_{= \text{feasibility cap } r^{FC}} \tag{A10}$$

$$= (1 - \theta(R))r^{BE} + \theta(R)r^{FC}, \tag{A11}$$

where the second equality follows that $\frac{\Pi_{total}}{s(p_l(R),m)L} = r^{FC} - r^{BE}$.

Here, the optimal price r^* is a convex combination of the break-even price r^{BE} and the feasibility cap r^{FC}. The participation constraint of both parties is always satisfied because the optimal price r^* is always bounded by the feasibility cap r^{FC} and the break-even price r^{BE}.

A.1.5. Proof of Proposition 2: Optimal Debt Spread and Relationship

From the optimal price r^* in Lemma (3), we have

$$\frac{\partial r^*}{\partial R} = (1 - \theta(R))\frac{\partial r^{BE}}{\partial R} + \theta'(R)(r^{FC} - r^{BE}). \tag{A12}$$

Given $r^{BE} = \frac{L+c(m)}{s(p_l(R),m)L} - 1$ and $s(p_l(R), m) = p_l(R) + (1 - p_l(R))\phi(m)$, we have

$$\frac{\partial r^{BE}}{\partial R} = -\frac{L + c(m)}{s(p_l(R), m)^2 L}(1 - \phi(m))\delta(p_{l,0}, \lambda) \leq 0, \tag{A13}$$

where the inequality follows that $\phi(m) \in [0, 1)$ and $\delta(p_{l,0}, \lambda) \in [0, 1 - p_{l,0}]$.

A.1.6. Proof of Lemma 4: Optimal Loan Size and Monitoring Intensity

The lender's optimal decision is to choose the optimal loan size L^* and monitoring intensity m^* to maximize the total surplus Π_{total}:

$$\max_{L,m} \Pi_{total} = s(p_l(R), m)X_S - L - c(m). \tag{A14}$$

For the loan size L, the first-order condition gives

$$\frac{\partial \Pi_{total}}{\partial L} = -1 < 0. \tag{A15}$$

Given the participation constraint in Lemma (1), the lender chooses the smallest feasible loan size $L^* = L_{min} = \phi(\underline{m})X_s - c(\underline{m})$.

For the monitoring intensity m, the first-order condition gives

$$\frac{\partial \Pi_{total}}{\partial m} = (1 - p_l(R))X_S\phi'(m^*) - c'(m^*) = 0. \tag{A16}$$

The optimal monitoring intensity m^* is uniquely determined because of the assumption that $\phi''(m) < 0$ and $c''(m) > 0$.

A.1.7. Proof of Proposition 3: Optimal Contract Terms and Relationship

From the optimal loan size L^* in Lemma (4), we have

$$\frac{\partial L^*}{\partial R} = 0. \tag{A17}$$

For the optimal monitoring intensity m^*, we differentiate the first-order condition with respect to m^*:

$$(1 - p_l(R))X_S\phi''(m^*) - \delta(p_{l,0}, \lambda)X_S\phi'(m^*)\frac{\partial R}{\partial m^*} = c''(m^*). \tag{A18}$$

Rearranging the terms, we have

$$\frac{\partial R}{\partial m^*} = \frac{(1-p_l(R))X_S\phi''(m^*) - c''(m^*)}{\delta(p_{l,0},\lambda)X_S\phi'(m^*)} < 0. \tag{A19}$$

where the inequality follows that $\phi'(m^*) > 0$ and $\phi''(m^*) < 0$. This is equivalent to

$$\frac{\partial m^*}{\partial R} = \frac{\delta(p_{l,0},\lambda)X_S\phi'(m^*)}{(1-p_l(R))X_S\phi''(m^*) - c''(m^*)} < 0. \tag{A20}$$

A.1.8. Proof of Proposition 4: Startup's Profit and Relationship

The startup's profit is also proportional to the total surplus Π_{total}, $\Pi_i = (1-\theta(R))\Pi_{total}$. The derivative of the startup's profit Π_i with respect to the relationship R is given by

$$\frac{\partial \Pi_i}{\partial R} = (1-\theta(R))\frac{\partial \Pi_{total}(L^*, m^*; p_l(R))}{\partial R} - \theta'(R)\Pi_{total}(L^*, m^*; p_l(R)). \tag{A21}$$

Now let's consider $\frac{\partial \Pi_{total}(L^*, m^*; p_l(R))}{\partial R}$.

$$\begin{aligned}\frac{\partial \Pi_{total}(L^*, m^*; p_l(R))}{\partial R} &= \left((1-\phi(m^*))\delta + (1-p_l(R))\phi'(m^*)\frac{\partial m^*}{\partial R}\right)X_s - c'(m^*)\frac{\partial m^*}{\partial R} && \text{(A22)}\\ &= (1-\phi(m^*))\delta X_s + ((1-p_l(R))\phi'(m^*)X_s - c'(m^*))\,\frac{\partial m^*}{\partial R} && \text{(A23)}\\ &= (1-\phi(m^*))\delta X_s, && \text{(A24)}\end{aligned}$$

where the last equality follows from the optimal monitoring intensity m^* in Lemma (4).

A.1.9. Proof of Corollary 1: Market Power, Loan Spread, and Startup's Profit

First, let's consider the loan spread r^*. From Proposition (2), we have

$$\begin{aligned}&\frac{\partial r^*}{\partial R} = (1-\theta(R))\frac{\partial r^{BE}}{\partial R} + \theta'(R)(r^{FC} - r^{BE}) > 0 && \text{(A25)}\\ \Longleftrightarrow\ &(1-\theta(R))\frac{\partial r^{BE}}{\partial R} + \theta'(R)\frac{\Pi_{total}}{s(p_l(R), m^*)L^*} > 0 && \text{(A26)}\\ \Longleftrightarrow\ &\frac{\theta'(R)}{1-\theta(R)} > -\frac{\partial r^{BE}}{\partial R}\frac{s(p_l(R), m^*)L^*}{\Pi_{total}}. && \text{(A27)}\end{aligned}$$

We now organize the terms on the right-hand side.

$$\frac{\theta'(R)}{1-\theta(R)} > -\frac{\partial r^{BE}}{\partial R}\frac{s(p_l(R),m^*)L^*}{\Pi_{total}} \tag{A28}$$
$$= -\frac{L+c(m^*)}{Ls(p_l(R),m^*)^2}(1-\phi(m^*))\delta(p_{l,0},\lambda)\frac{s(p_l(R),m^*)L^*}{\Pi_{total}} \tag{A29}$$
$$= -\frac{L+c(m^*)}{s(p_l(R),m^*)}\frac{(1-\phi(m^*))\delta(p_{l,0},\lambda)}{\Pi_{total}}. \tag{A30}$$

Then let's consider the startup's profit Π_i. From Proposition (4), we have

$$\frac{\partial \Pi_i}{\partial R} = (1-\theta(R))\frac{\partial \Pi_{total}(L^*,m^*;p_l(R))}{\partial R} - \theta'(R)\Pi_{total}(L^*,m^*;p_l(R)) > 0 \tag{A31}$$
$$\iff \frac{\theta'(R)}{1-\theta(R)} < \frac{\partial \Pi_{total}(L^*,m^*;p_l(R))}{\partial R}\Pi_{total}(L^*,m^*;p_l(R)). \tag{A32}$$

Now we organize the terms on the right-hand side.

$$\frac{\theta'(R)}{1-\theta(R)} < \frac{\partial \Pi_{total}(L^*,m^*;p_l(R))}{\partial R}\Pi_{total}(L^*,m^*;p_l(R)) \tag{A33}$$
$$= X_s\frac{(1-\phi(m^*))\delta(p_{l,0},\lambda)}{\Pi_{total}(L^*,m^*;p_l(R))}. \tag{A34}$$

Putting together, we have

$$\frac{L^*+c(m^*)}{s(p_l(R),m^*)}\frac{(1-\phi(m^*))\delta(p_{l,0},\lambda)}{\Pi_{total}(L^*,m^*;p_l(R))} < \frac{\theta'(R)}{1-\theta(R)} < X_s\frac{(1-\phi(m^*))\delta(p_{l,0},\lambda)}{\Pi_{total}(L^*,m^*;p_l(R))}. \tag{A35}$$

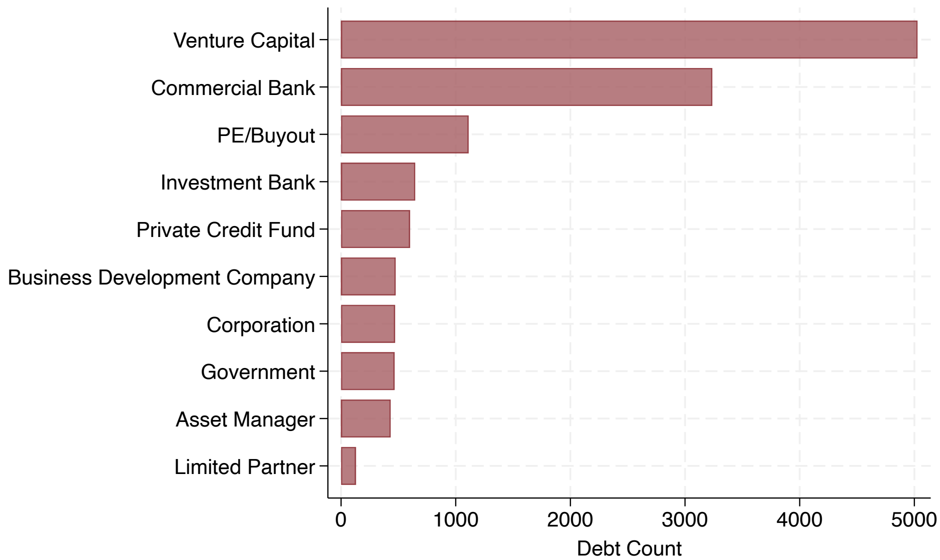
To make sure the interval is nonempty, we need to ensure that

$$\frac{L^*+c(m^*)}{s(p_l(R),m^*)} < X_s \iff \Pi_{total}(L^*,m^*;p_l(R)) \equiv s(p_l(R),m^*)X_s - L^* - c(m^*) > 0. \tag{A36}$$

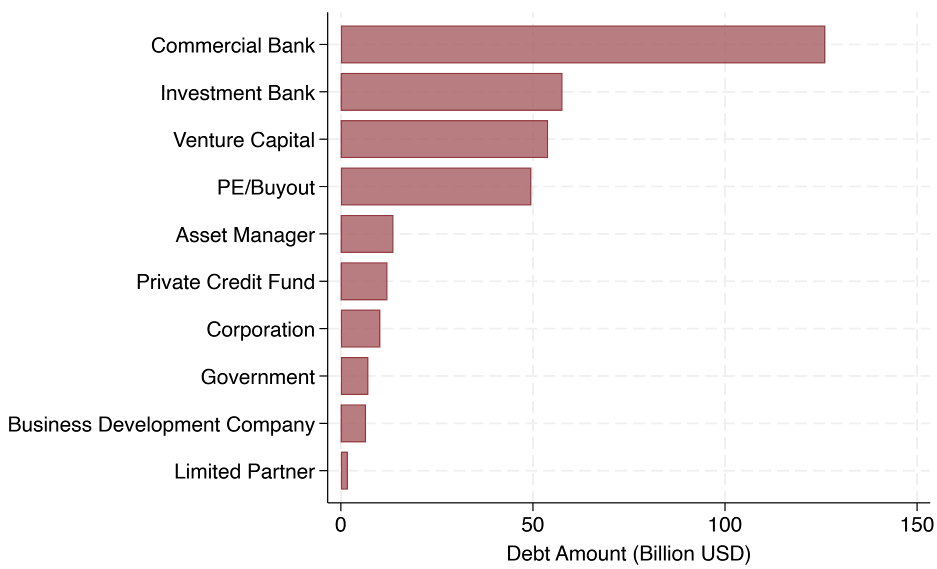
This is always true because of the participation constraint in Lemma (1).

Figure A.1. Venture Debt by Lender Type

Panel (a): # Deals



Panel (b): Deal Amount



Notes. This figure presents venture debt activity by lender type. Panel (a) shows the total number of venture debt deals by lender type. Panel (b) reports the aggregate debt amount (in million USD) by lender type. Lender types include commercial banks, investment banks, corporations, limited partners, governments, venture capital, private equity/buyout funds, business development companies (BDCs), private credit funds, and asset managers.

Table A.1. Top 50 Venture Debt Lenders

Order	Lender Name	Lender Location	Lender Type	# Debt	Amount ($MM)	I(Relationship)	Share of Relation
1	Western Technology Investment	Portola Valley, CA	Venture Capital	1,175	5,140	0.885	0.685
2	SVB Financial Group	Santa Clara, CA	Commercial Bank	716	7,119	0.887	0.580
3	TriplePoint Capital	Menlo Park, CA	Venture Capital	314	2,413	0.994	0.796
4	Hercules Capital	San Mateo, CA	BDC	254	3,852	0.862	0.503
5	Kreos Capital	London, United Kingdom	Venture Capital	221	1,506	0.850	0.502
6	Square 1 Bank	Durham, NC	Commercial Bank	183	827	0.746	0.365
7	Monroe Capital	Chicago, IL	Investment Bank	166	1,866	0.761	0.369
8	North Carolina Biotechnology Center	Research Triangle Park, NC	Venture Capital	161	38	0.631	0.573
9	Trinity Capital	Phoenix, AZ	BDC	160	1,109	0.757	0.396
10	Horizon Technology Finance BDC	Farmington, CT	BDC	160	385	0.726	0.333
11	JP Morgan Chase	New York, NY	Commercial Bank	157	19,077	0.549	0.357
12	InnoVen Capital	Mumbai, India	Venture Capital	153	1,803	0.923	0.553
13	Lighter Capital	Seattle, WA	Venture Capital	142	41	0.445	0.338
14	Comerica Bank	Dallas, TX	Commercial Bank	138	1,043	0.633	0.299
15	Bank of America	Charlotte, NC	Commercial Bank	136	6,370	0.526	0.362
16	Oxford Finance	Alexandria, VA	Private Credit Fund	134	2,060	0.872	0.486
17	Bpifrance	Paris, France	Venture Capital	133	300	0.743	0.641
18	The Goldman Sachs Group	New York, NY	Investment Bank	131	10,373	0.821	0.556
19	Japan Finance Corporation	Tokyo, Japan	Venture Capital	128	203	0.837	0.639
20	European Investment Bank (Luxembourg)	Luxembourg, Luxembourg	Investment Bank	126	5,165	0.767	0.349
21	Bridge Bank	San Jose, CA	Commercial Bank	118	618	0.664	0.217
22	Barclays	London, United Kingdom	Commercial Bank	109	6,819	0.614	0.364
23	Espresso Capital	Toronto, Canada	Private Credit Fund	105	326	0.683	0.352
24	ORIX Growth Capital	New York, NY	Venture Capital	96	734	0.753	0.362
25	Ares Management	Los Angeles, CA	PE/Buyout	88	1,669	0.762	0.395
26	Wells Fargo	San Francisco, CA	Commercial Bank	86	3,655	0.435	0.244
27	MidCap Financial	Bethesda, MD	Private Credit Fund	80	1,487	0.709	0.290
28	MMV Capital Partners	Toronto, Canada	Venture Capital	77	195	0.838	0.497
29	Runway Growth Capital	Menlo Park, CA	Venture Capital	75	1,380	0.800	0.546
30	Canadian Imperial Bank of Commerce	Toronto, Canada	Commercial Bank	74	1,438	0.576	0.258
31	PNC	Pittsburgh, PA	Commercial Bank	74	559	0.469	0.296
32	GE Capital	Norwalk, CT	Commercial Bank	72	902	0.641	0.396
33	Viola Credit	Herzliya, Israel	Venture Capital	70	1,645	0.791	0.490
34	Deutsche Bank	Frankfurt, Germany	Commercial Bank	69	4,553	0.625	0.338
35	Trifecta Capital	Gurgaon, India	Venture Capital	69	1,168	0.926	0.533
36	Tennenbaum Capital Partners	Santa Monica, CA	PE/Buyout	68	1,013	0.866	0.289
37	Fondation pour l'Innovation Technologique	Lausanne, Switzerland	Limited Partner	68	26	0.924	0.701
38	BlackRock	New York, NY	PE/Buyout	66	3,898	0.954	0.547
39	Credit Suisse	Zurich, Switzerland	Investment Bank	62	5,523	0.706	0.408
40	HSBC Holdings	London, United Kingdom	Commercial Bank	60	3,209	0.627	0.301
41	Golub Capital	New York, NY	PE/Buyout	59	2,705	0.797	0.475
42	Escalate Capital Partners	Austin, TX	Venture Capital	58	454	0.732	0.361
43	U.S. Bank	Minneapolis, MN	Commercial Bank	57	576	0.280	0.186
44	Citigroup	New York, NY	Investment Bank	56	5,656	0.509	0.335
45	Wellington Financial	Toronto, Canada	Venture Capital	55	368	0.787	0.486
46	Multiplier Capital	Washington, DC	PE/Buyout	54	155	0.796	0.324
47	BNP Paribas	Paris, France	Commercial Bank	53	2,849	0.571	0.288
48	Morgan Stanley	New York, NY	Investment Bank	52	5,410	0.837	0.453
49	Chase Bank	New York, NY	Commercial Bank	52	487	0.314	0.124
50	SaaS Capital	Seattle, WA	PE/Buyout	50	97	0.302	0.137

Notes. This table presents the top 50 venture debt lenders ranked by the number of deals. For each lender, we report the location of its headquarters, the lender type, the number of venture debt deals in which it participated, the total debt amount provided across all deals, and the average relationship score.

Table A.2. Summary Statistics on Venture Debt Startups and Control Sample

	All Sample (N = 56,273)	VD Sample (N = 7,280)	Control Sample (N = 48,993)
ln(Employment)	3.323	3.519	3.294
ln(Cum. Fin Amount)	2.259	2.379	2.241
ln(Age)	3.136	3.144	3.135
I(All VC Deals)	0.116	0.107	0.118
ln(All VC Deal Amount)	0.206	0.187	0.208
ln(Patent)	0.075	0.082	0.074
ln(CW Patent)	0.113	0.124	0.111

Notes. This table presents summary statistics on venture debt startups and the control sample. The VD sample consists of startups that received venture debt, and the control sample consists of matched firms that did not receive venture debt. Variables include the log number of employment, the log value of cumulative financing amount, the log value of age, an indicator for whether the firm received any VC deal, the log value of VC deal amounts, the log number of patents, and the log number of citation-weighted patents.

Table A.3. Venture Debt Relationship, Contract Amount, and Maturity

$Y_{d,i}$ =	(1)	(2)	(3)	(4)	(5)
	ln(Debt Amount)			ln(Maturity)	
	OLS	IV		OLS	IV
I(Relationship)$_d$	-0.357***	-0.231		-0.249***	-0.286**
	(0.048)	(0.157)		(0.042)	(0.117)
ln(Employment)$_{d,i}$	0.333***	0.316***		0.005	0.019
	(0.025)	(0.026)		(0.016)	(0.017)
ln(Cum. Fin Amount)$_{d,i}$	0.518***	0.526***		0.009	0.006
	(0.025)	(0.027)		(0.015)	(0.018)
ln(Age)$_{d,i}$	0.126***	0.126***		0.125***	0.121***
	(0.039)	(0.040)		(0.033)	(0.034)
1(Same City as Lender)$_{d,i}$	0.778***	0.769***		0.402***	0.422***
	(0.111)	(0.115)		(0.105)	(0.111)
ln(Distance to Lender)$_{d,i}$	0.132***	0.130***		0.041***	0.043***
	(0.013)	(0.013)		(0.010)	(0.010)
Observations	7,238	6,972		2,829	2,652
R-squared	0.568	0.334		0.294	0.041
Deal-Facility Round FE	Yes	Yes		Yes	Yes
Industry-Year FE	Yes	Yes		Yes	Yes
Country-Year FE	Yes	Yes		Yes	Yes
Mean DV	1.540	1.541		1.192	1.166
First-Stage Coefficients and F-Statistic					
VCs' Lender HHI		-0.540***			-0.604***
		(0.023)			(0.037)
F-Statistic		545.2			260.1

Notes. This table examines the effect of venture debt relationships on loan contract terms at the facility level. The dependent variables are log value of debt amount in Columns (1)-(2) and log value of maturity (in years) in Columns (3)-(4). I(Relationship)$_d$ is an indicator variable of whether the lender is involved with the startup's VC investors. We control for the log number of employment, the log value of cumulative financing amount, the log value of age, an indicator for whether the lender and borrower are headquartered in the same city, and the log geographic distance between lender and borrower headquarters. For each outcome, we report the results using both OLS and IV regressions, as described in Section 5.1. The model includes deal-facility-round fixed effects, industry-year fixed effects, and country-year fixed effects. Standard errors are clustered at the startup level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.