Credit Commitments by Nonbanks*

Jing Huang David X. Xu

This version: *October 2026*

Abstract

Despite the secular shift to nonbank lending, banks retain a distinctive advantage in providing credit lines (Kashyap, Rajan, and Stein, 2002). We document a new fact about nonbank lending: business development companies (BDCs) extend substantial credit commitments to borrowers, with off-balance-sheet commitments growing faster than total BDC assets. These commitments are concentrated, exposing BDCs to undiversified borrower liquidity shocks, a risk they manage with credit lines from banks. We develop a credit chain model of layered liquidity insurance and show that this chain is not a pure pass-through of bank liquidity: it delivers only partial insurance—even when direct bank lending offers full insurance—because managing undiversified shocks with bank credit raises nonbanks' bankruptcy costs. We provide evidence consistent with our model's implications.

JEL Classification: G21, G23, G32

Keywords: Nonbanks, private credit, business development companies (BDCs), credit lines, liquidity insurance

*Huang: Mays Business School, Texas A&M University; email: jing.huang@tamu.edu; Xu: Cox School of business, Southern Methodist University. Email: davidxu@smu.edu. For helpful comments, we thank Zhiguo He, Gregor Matvos, Richard Lowery, Stephan Luck, Huan Tang, and participants at the Private Equity Research Symposium (Oxford), Stanford SITE Financial Regulation, the CEPR European Summer Symposium in Financial Markets (Gerzensee), and the Lone Star Finance Conference. Qi An, Saranya Sudharsan, Haokun Wei, and Mingzhi Xie provided excellent research assistance. All errors are our own.

The secular decline in banks' balance-sheet lending has blurred the boundaries between banks and nonbanks in financial intermediation (Buchak, Matvos, Piskorski, and Seru, 2024). For example, private credit has grown rapidly in middle-market corporate lending, the nonbank share of residential mortgage originations has increased substantially, and fintech lenders have expanded in small-business lending.[1] Yet banks retain a distinctive advantage in providing credit lines, owing to their access to deposit funding (Kashyap, Rajan, and Stein, 2002). Credit lines insure borrowers against liquidity shocks and thereby improve real efficiency (Holmström and Tirole, 1998), but providing such insurance is challenging for nonbanks, which lack stable deposit funding.

In this paper, we document a new fact about the provision of liquidity insurance. Using novel hand-collected data, we show that business development companies (BDCs), a large segment of nonbank lenders, issue substantial credit commitments to their portfolio borrowers in the form of revolving credit lines and delayed-draw term loans. We find that these off-balance-sheet commitments have grown rapidly in recent years and become economically significant, rising from near zero in 2005 to roughly 15% of total BDC balance sheet assets by the end of 2025. This fact suggests that credit commitments provided by nonbanks have become an increasingly important source of corporate liquidity insurance.

A natural question is how BDCs provide these credit commitments and manage the associated liquidity risk. As Holmström and Tirole (1998) show, when liquidity shocks are purely idiosyncratic and fully diversifiable, any intermediary with commitment power can provide liquidity insurance by pooling borrowers and raising funding from spot markets. Do BDCs simply diversify idiosyncratic shocks, or do they ultimately rely on a stable source of funding from other intermediaries? To answer this question, we combine detailed facility-level data on BDCs' commitment books with their loan portfolio holdings, balance sheets,

[1] See Block, Jang, Kaplan, and Schulze (2024); Buchak, Matvos, Piskorski, and Seru (2018); He, Huang, and Zhou (2023); Huang (2026).

cash flow statements, and importantly, off-balance-sheet credit lines that BDCs receive from third-party lenders, which are mostly banks.

We establish two empirical patterns. First, BDCs' credit commitments expose them to large and volatile liquidity shocks from their borrowers. We measure the BDC-level liquidity shocks by tracking individual credit facilities in the BDC's commitment book and estimate their time-series volatility. These shocks are sizable: a one-standard-deviation quarterly shock would exhaust the BDC's cash holdings in about 15% of BDC-quarters, and the magnitude is substantially more pronounced for BDCs with greater commitment books.

Liquidity shocks are volatile at the BDC level because commitment books are concentrated and borrower drawdowns are not fully idiosyncratic. Unfunded commitments are substantially more concentrated in certain borrower segments than the same BDC's on-balance-sheet loan portfolio. Because liquidity shocks are correlated within a segment, this concentration limits the benefit of pooling: the volatility of liquidity shocks experienced by individual BDCs is roughly three times as large as that of a fully diversified benchmark. Moreover, borrower liquidity shocks carry a common component that cannot be diversified away, with the 2020Q1 COVID episode as a visible example. A concentrated book with correlated borrower liquidity shocks exposes the BDC to undiversified liquidity risk.

Second, BDCs manage this liquidity risk primarily through bank credit lines they receive as borrowers. The undrawn capacity of bank credit lines acts as an economically important liquidity backstop for unfunded commitments, giving rise to a chain of liquidity insurance. However, this chain is a potential source of fragility amplification that regulators have flagged—the FSOC 2024 Annual Report (Box E) warns of a "dash for liquidity" in which firms draw on their nonbank lenders, who in turn draw on their bank credit facilities. To our knowledge, we provide the first study to examine liquidity insurance along this chain.

With BDCs as a laboratory, our evidence raises deeper questions about the growing

provision of liquidity insurance by nonbanks. Given nonbanks' exposure to undiversified borrower liquidity shocks and their reliance on bank credit lines, does the liquidity insurance they provide differ fundamentally from that of traditional banks? Or, is the credit chain only a pure pass-through of the bank's liquidity provision?

To answer these questions, we develop a model of layered credit-line provision that builds on Holmström and Tirole (1998). Firms hit by liquidity shocks are costly to finance ex post. Credit lines insure against such shocks: an intermediary pools many borrowers ex ante, and the spare liquidity of those who do not draw funds the drawdowns of those who do. Because spot markets lack such commitment and self-insurance through cash is costly, firms seek credit lines for liquidity management. Motivated by our evidence, a BDC extends credit to a finite number of firms, providing a first layer of insurance by pooling liquidity shocks within its portfolio. Because this leaves undiversified liquidity risk, the BDC relies on a committed credit line from a bank to fund borrower drawdowns. The bank credit line forms the second layer of insurance: pooling across its large and diversified book, the bank channels the spare liquidity of its unshocked borrowers to absorb the BDC's residual liquidity risk.

To study liquidity provision along the credit chain, we first show that a direct bank lending benchmark delivers full insurance by pooling across a large and diversified book. Because direct lending is costly under regulatory capital rules, banks instead finance these firms indirectly through BDCs along the credit chain. Although a BDC can draw its bank credit line whenever its portfolio firms draw, the chain is not a pure pass-through of the bank's liquidity provision. It delivers only *partial insurance*, owing to the BDC's bankruptcy cost, which reflects its undiversified commitment book and the lack of a public backstop for nonbanks. Coverage is costly in the very states where it is most used: widespread draws load the BDC with debt precisely when its portfolio collections are weakest, pushing it into insolvency. The BDC therefore takes a smaller bank credit line, rationing borrower

drawdowns in widespread-shock states to limit its own default. Notably, this still allows for diversification when only a few borrowers have large shocks and the bank facility is not exhausted.

We hence add contracting frictions to the classic framework of Holmström and Tirole (1998): providing insurance loses money in certain states, and full insurance is not optimal when the insurer is subject to debt-contract frictions. The same frictions make the middle layer socially costly when shocks are *undiversified*, incurring an extra deadweight loss (analogous to the monitoring costs when shocks are not idiosyncratic, as in Diamond, 1984).

We find evidence consistent with BDCs providing only partial liquidity insurance. Across BDC-quarters, our estimates indicate that a one-dollar increase in the BDC's unfunded commitments is associated with significantly less than one dollar of additional liquidity, whether measured by undrawn bank credit alone or together with cash holdings.[2] Hypothetical BDC-level liquidity shocks with plausible magnitudes could exhaust the estimated liquidity backstop, suggesting that BDCs may not fully accommodate widespread drawdown requests. Moreover, when liquidity needs rise among highly-leveraged peer firms in an industry, borrowers of BDCs with tighter liquidity conditions draw significantly less than borrowers of other BDCs from the same industry. This finding implies that BDCs ration drawdowns ex post when they do not have enough liquidity to accommodate all borrowers' cash needs.

Partial insurance carries a further theoretical implication: an *externality* among the firms sharing the constrained pool—in essence, a tragedy of the commons. A firm that shirks in liquidity management does not internalize that its own draw crowds out coverage for the others, so equilibrium effort falls below the socially optimal level. This externality arises only when the liquidity pool is constrained and is thus specific to nonbanks; banks, by contrast, hold diversified books, access deposit funding, and expect intervention in a crisis,

[2]Statutory asset-coverage requirements, if binding, may further limit the BDC's ability to use undrawn bank credit.

so their committed capacity rarely binds. This connects to Bräuning and Ivashina (2026), who identify a related liquidity-pool problem for banks: unlike their *ex-post* credit-line run, ours is an *ex-ante* distortion of firms' liquidity management.

Related Literature

Our paper relates to several strands of literature, most closely the literature on *credit lines and bank liquidity provision*. Extending the diversification logic of Diamond (1984) to liquidity provision, Holmström and Tirole (1998) show that credit lines deliver the second-best allocation under idiosyncratic liquidity shocks.[3] Banks, with stable funding supplied by "sleepy" depositors (Hanson, Shleifer, Stein, and Vishny, 2015) and, in crisis, government support (Acharya and Mora, 2015), are argued to have a structural advantage in providing credit lines. In fact, liquidity provision is widely identified as a defining advantage of banks over nonbank intermediaries, and rationalizes the very existence of bank balance-sheet lending which combines credit extension with payment services (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006, 2009; Pennacchi, 2006). Connecting this bank-centered view to the post-GFC migration of credit from banks to nonbanks (Buchak, Matvos, Piskorski, and Seru, 2018, 2024; Irani, Iyer, Meisenzahl, and Peydró, 2021), we study the growing extension of credit commitments by nonbanks and its implications for liquidity provision.[4]

We also speak to the *empirical literature on credit lines* (e.g., Sufi, 2009; Greenwald, Krainer, and Paul, 2025; Demiroglu and James, 2011; Chodorow-Reich, Darmouni, Luck,

[3]For other theories of credit lines, see Acharya, Almeida, Ippolito, and Perez-Orive (2014) on monitored liquidity insurance and Donaldson, Koont, Piacentino, and Vanasco (2024) on the role of contingent commitment in mitigating debt dilution.

[4]Consistent with this view, nonbank lenders typically extended corporate credit in the form of term loans instead of credit commitments (Bord and Santos, 2012; Berlin, Nini, and Yu, 2020; Haque, Mayer, and Stefanescu, 2024), and existing studies on nonbank lending have largely focused on the origination and secondary market trading of term loans (e.g., Nadauld and Weisbach, 2012; Lim, Minton, and Weisbach, 2014; Bruche, Malherbe, and Meisenzahl, 2020; Bruche, Meisenzahl, and Xu, 2026; Ivashina and Sun, 2011; Elkamhi and Nozawa, 2022; Xu, 2026).

and Plosser, 2022). Most relevant to our paper is whether credit lines cover idiosyncratic or aggregate liquidity shocks, because diversifying idiosyncratic shocks only requires an intermediary with commitment, not necessarily a bank. Along this line, Acharya, Almeida, and Campello (2013) point to a prioritization of idiosyncratic shocks: firms with greater aggregate-risk exposure obtain credit lines on worse terms and substitute toward cash. Aggregate shocks are nonetheless covered to some degree: Acharya, Engle, Jager, and Steffen (2024) document that stocks of banks that had committed credit lines underperformed during the COVID-19 shock.

Our focus on BDCs' reliance on bank credit lines as a liquidity backstop connects to the literature on *intermediation chains*. Acharya, Gopal, Jager, and Steffen (2025) document that bank lending to nonbank financial intermediaries has grown rapidly, mainly in the form of committed credit lines (see also Acharya, Cetorelli, and Tuckman, 2026). As the upstream layer of the chain, bank credit has been studied as a key funding source for mortgage originators (Jiang, 2023), BDCs (Chernenko, Ialenti, and Scharfstein, 2025; Haque, Jang, and Wang, 2025), and nonbanks more broadly (Xu, 2025). The literature offers several explanations for why credit chains arise, including regulatory arbitrage (Chernenko, Ialenti, and Scharfstein, 2025), asymmetric information (Glode and Opp, 2016), and insulation against rollover risk (He and Li, 2026). While this literature has studied banks' liquidity provision to nonbanks, our contribution is a *two-layered* liquidity-insurance chain in which the nonbank's own liquidity need is endogenous to the commitments it has extended to borrower firms.

The implication that nonbanks' constrained liquidity pool induces lax liquidity management is, in essence, a tragedy of the commons (Hardin, 1968). It connects to Bräuning and Ivashina (2026) and Ivashina and Scharfstein (2010): theirs is an *ex-post* run on committed capacity, whereas ours is an *ex-ante* distortion in firms' liquidity management.

Finally, we use BDCs as a laboratory to study nonbanks and hence connect to the growing

literature on private credit and BDCs. This literature has studied private credit lenders' balance sheets (Matvos, Piskorski, and Seru, 2026), lending technology (Jang, Kim, Sufi, and Chen, 2025), loan contractual terms (Chernenko, Erel, and Prilmeier, 2022; Block, Jang, Kaplan, and Schulze, 2024; Jang, 2026), as well as lending dynamics and market discipline (Davydiuk, Marchuk, and Rosen, 2024a,b). Notably, Haque, Mayer, and Stefanescu (2024) document a within-borrower complementarity between term loans provided by nonbanks and credit lines provided by banks. Our paper contributes to this literature by examining private credit lenders' off-balance-sheet credit commitments and the intermediation chain that facilitates this liquidity provision. In contemporaneous work, Flanagan and Jang (2026) argue that alternative liquidity sources, such as uncalled investor capital, may also support nonbank provision of credit lines.

1 Data

1.1 Institutional Background

Business development companies (BDCs) are closed-end investment vehicles regulated under the Investment Company Act of 1940. To be eligible, a BDC must hold at least 70% of its assets in qualifying assets, typically financial claims of U.S. middle-market operating companies. BDCs invest across the corporate capital structure but mainly hold senior secured loans. Most BDCs elect to be taxed as regulated investment companies (RICs), which avoid corporate-level tax by distributing at least 90% of their investment company taxable income to shareholders each year. BDCs also face a 200% minimum statutory asset-coverage requirement that constrains their own borrowing.[5]

BDCs are a large segment of the private credit market, which is one of the fastest-growing

[5]Since 2018, BDCs have been allowed to reduce the asset coverage ratio to 150%.

parts of the financial system, now with over $1 trillion in the United States.[6] There are three types of BDCs: exchange-listed BDCs, whose equity shares trade on stock exchanges; non-traded BDCs, which offer periodic share purchases and redemptions (commonly capped near 5% of net asset value per quarter) to retail investors; and private BDCs, which are raised via private placement offerings to accredited investors. All BDCs are subject to public disclosure requirements and file periodic reports with the SEC.

The universe of BDCs we identify from SEC EDGAR comprises 245 unique BDCs between 2005Q1 and 2025Q4, with combined total assets of roughly $550 billion as of 2025Q4. These BDCs offer a transparent window into the opaque private credit market. Figure IA.1 in the Internet Appendix shows the total number and assets of these listed and non-listed BDCs.

1.2 Data Sources

We assemble four datasets: (i) a BDC-quarter panel of balance-sheet, cash-flow, and off-balance-sheet commitment items; (ii) the BDC's commitment book with unfunded amounts at the BDC-quarter-borrower-facility level; (iii) a quarterly panel of bank credit lines that BDCs obtain as borrowers; and (iv) loan portfolio holdings at the BDC-quarter-borrower-facility level. Datasets (i)–(iii), which cover BDCs' commitments and their bank funding, are hand-collected from SEC EDGAR filings. We supplement them with data from PitchBook, FactSet, Compustat, S&P Capital IQ (CIQ), and the FFIEC Call Report. Internet Appendix IA.1 provides details on the collection and processing of these datasets.

BDC-quarter panel. We identify the universe of BDCs through Form N-54A, N-54B, and N-54C filings on EDGAR, which respectively elect, amend, and withdraw BDC status under the Investment Company Act of 1940. The sample consists of $6,398$ BDC-quarters across

[6] See "Bank Lending to Private Credit: Size, Characteristics, and Financial Stability Implications," FEDS Notes, Federal Reserve Board, May 2025.

245 unique BDCs over 2005Q1–2025Q4 in which the BDC has an active N-54A election and reports balance-sheet items. The main BDC-quarter variables are the BDC's total unfunded commitments extended to borrower firms; balance-sheet items including total assets, total debt, total equity, and cash holdings (cash and equivalents); and statement-of-cash-flow items including operating, investing, and financing cash flow subtotals.

Unfunded amount in commitment books. For the subset of BDC-quarters in which the filing's commitments-and-contingencies note discloses a detailed breakdown of the unfunded loan commitments, we hand-collect each borrower firm's unfunded amount, the type of credit commitment (revolving credit facility, delayed-draw term loan, or other), and other reported terms. We use DDTL to refer to "delayed-draw term loan" henceforth. The resulting dataset covers 3,749 BDC-quarters and 167,389 facility-level observations. For analyses that use the change in unfunded commitment as a proxy for drawdown activity, we restrict the sample to borrower-facility-quarters with lagged unfunded above $1 million to avoid small-denominator noise. To identify borrowers in these commitment books and merge their firm characteristics, we link each borrower to a PitchBook company identifier (see Internet Appendix IA.1.6).

Quarterly panel of bank credit lines. BDCs disclose each revolving facility they obtain as borrowers in a nonstandardized textual borrowings note. Because the lead lenders are predominantly banks, we refer to these facilities as bank credit lines. We assign a credit-line identifier (CLID) to each facility and hand-collect, at each filing date, the credit limit, drawn balance, undrawn capacity, lender identities (administrative agent and other syndicate members), interest-rate terms (benchmark and spread), maturity, and any contractually specified accordion provision. We also build a complementary event panel recording each facility's inception, amendments, accordion exercises, terminations, and replacements. The CLID-quarter panel covers 9,118 CLID-quarters across 776 unique CLIDs and 200 BDCs over 2005Q1–2025Q4. Internet Appendix IA.4 summarizes the lender composition, the event

panel, and the prevalence of accordion features.

Portfolio holdings. We obtain data on BDC portfolio holdings (term loans, revolvers, DDTLs, bonds, equity, structured products, and other debt) at the BDC-quarter-borrower-facility level from PitchBook, linked to BDCs via SEC Central Index Keys (CIKs). Holdings data are available for 5,811 BDC-quarters in our sample. We also draw on portfolio holdings from FactSet to facilitate linking borrowers between the commitment book and the portfolio holdings datasets.

Supplementary data. We use the FFIEC's Consolidated Reports of Condition and Income (Call Reports) to construct the bank-quarter variables. We use S&P Capital IQ (CIQ) Capital Structure data and Compustat to construct quarterly aggregate public-firm drawdown factors, with details in Internet Appendix IA.2.2. We also cross-validate the hand-extracted BDC balance-sheet items against Compustat and CIQ where coverage permits.

1.3 Summary Statistics

Table 1 summarizes the BDC-quarter panel. Panel A presents all 6,435 BDC-quarters. The average BDC holds $1.6 billion in total assets, with a median of $524 million and the 95th percentile exceeding $6.0 billion. BDCs use relatively low financial leverage: average equity is $851 million, against average total debt of $695 million. As a lender, the average BDC extends $150 million of total unfunded commitments to borrowers, with a large right tail reaching $547 million at the 95th percentile. As borrowers, BDCs receive on average 1.5 bank credit lines with an average total credit limit of $591 million, of which on average $270 million remains undrawn.

Panel B restricts to the 3,749 BDC-quarters that disclose a borrower-level commitment book. The average BDC reports 47 outstanding unfunded commitments to portfolio companies, with an average unfunded amount per commitment of $4.1 million (median $2.9 million).

These magnitudes are consistent with BDCs lending to middle-market borrowers below the size of typical syndicated loans. Panel C reports the fair-value composition of BDC portfolio holdings. On average, senior secured loans (term loans, unitranche, and the drawn portion of revolvers and DDTLs) account for 74% of holdings. Equity stakes in operating portfolio companies account for 12%, joint-venture lending vehicles (e.g., senior loan funds and specialty-lending platforms, identified by issuer-name patterns) for about 1%, and other debt (subordinated, mezzanine, and unsecured) for the remaining 14%.

Table 2 summarizes the commitment book at the BDC-facility-quarter level. The sample contains 82,476 facility-quarters with at least $1 million of lagged unfunded amount. Panel A presents all commitment types. The average unfunded amount is $7.0 million, with a median of $3.2 million and a right tail reaching $24.8 million at the 95th percentile. The average drawdown rate ($-\%\Delta$Unfunded) is 2.8% per quarter, consistent with net drawdown on average. Borrowers actively draw commitments—that is, the unfunded amount decreases—in 33.8% of facility-quarters. The average time to maturity is 3.2 years. Panels B and C present revolvers and DDTLs separately. Revolvers are smaller than DDTLs on average ($5.4 million vs $9.3 million) but have a longer maturity (4.1 years vs 2.2 years). DDTLs are drawn more frequently (41.1% of commitment-quarters) than revolvers (25.8%), consistent with DDTLs serving as acquisition-financing facilities with targeted drawdown schedules.

2 Empirical Patterns

This section documents BDC credit commitments as an economically important and growing source of corporate liquidity insurance and establishes two empirical patterns. First, BDCs' commitment books expose them to volatile borrower liquidity shocks. Second, BDCs manage this liquidity risk using bank credit lines as a liquidity backstop. Together, these patterns motivate the credit chain that our model formalizes in Section 3, as well as its key premise

that BDCs' liquidity risk from borrowers is undiversified.

2.1 Economic Significance of BDCs' Unfunded Commitments

In Figure 1, blue bars plot the total amount of unfunded commitments BDCs provide to portfolio companies. This amount remained below $10 billion until 2021 but grew rapidly thereafter, reaching roughly $80 billion by 2025. The solid line shows that this nonbank liquidity insurance is also widespread: the fraction of BDCs providing unfunded commitments has risen from below 50% in the 2000s to over 90% by 2025.

The rapid increase in unfunded commitments reflects more than the growth of the BDC sector. In Figure 2, the blue line shows the ratio of BDCs' total unfunded commitments to their total on-balance-sheet assets. This ratio was below 5% in 2010 but has risen steadily to about 15% by 2025Q4, suggesting that liquidity provision has grown disproportionately relative to the size of BDCs. This trend is also unlikely to be driven by the corporate sector's increased demand for liquidity insurance. For comparison, the red line in the figure shows banks' commitments extended to corporate borrowers (commercial and industrial firms and financial institutions), divided by total bank assets.[7] In contrast to BDCs, the bank version of this ratio has grown modestly, fluctuating between 10% and 15% over the same period.

2.2 Borrower Liquidity Shocks at the BDC Level

When borrowers draw their unfunded commitments, the lender needs to deliver cash, so these commitments generate a liquidity risk for BDCs. In this subsection, we quantify liquidity shocks from BDC commitment books and identify two economic forces that drive the BDC-level exposure to those shocks. Given the nature of the data (see Internet Ap-

[7]These two ratios are not fully comparable due to differences in asset composition between BDCs and banks. Here we use them nonetheless to illustrate the time trends in corporate liquidity insurance provision.

pendix Section IA.2.1 for details), we proxy for cashflows related to drawdown activity using changes in unfunded commitments of continuing positions that are observed in consecutive quarters. We use two alternative measures of borrower liquidity shocks: a continuous measure $-\%\Delta Unfunded_{i,\ell,t} = -\Delta Unfunded_{i,\ell,t}/Unfunded_{i,\ell,t-1}$ for borrower i's drawdown of BDC ℓ's commitment in quarter t, and a binary indicator $\mathbf{1}\{\Delta Unfunded_{i,\ell,t} < 0\}$ for whether the borrower draws cash from the committed facility.

2.2.1 Liquidity Shocks from Commitment Books

To quantify the BDC-level quarterly liquidity shocks from the commitment book, we restrict the sample of BDC-borrower-quarter observations to BDC-quarters with at least five borrowers and to BDCs with at least 12 such quarterly observations. For each BDC in this sample, we compute the dollar-weighted average of $-\%\Delta Unfunded_{i,\ell,t}$ across the BDC's continuing borrowers and estimate the volatility of the BDC-level liquidity shocks by computing their time-series standard deviation across quarters. We then translate this percentage volatility into dollar magnitudes by multiplying the standard deviation by the BDC's lagged total unfunded commitments.[8]

Table 3 reports the estimated dollar volatility. For the median BDC-quarter in our sample, total unfunded commitments equal 6.9% of total assets, and the estimated cash outflow corresponding to one standard deviation of liquidity shock from the commitment book equals 24.5% of the BDC's lagged cash holdings. Despite a moderate magnitude at the median, this estimated outflow exceeds the BDC's cash holdings in 15.3% of BDC-quarters. The magnitude is also substantially larger for BDCs with greater commitment books: in the top tercile of BDC-quarters, the estimated volatility equals 55.7% of cash at the median and exceeds cash in 28.9% of BDC-quarters. As such, the unfunded commitments represent

[8]This calculation estimates the dollar size of the typical cashflow in the commitment book. It does not measure realized BDC-quarter total borrower drawdowns, which are not observable in the data.

a significant liquidity risk for BDCs, and managing this risk requires liquidity beyond cash holdings.

2.2.2 Concentrated Commitments Expose BDCs to Undiversified Shocks

Diversification of borrower-specific liquidity shocks could reduce the volatility of liquidity shocks at the BDC level. But if a BDC's commitment book is concentrated in a few borrower segments, and if liquidity shocks are correlated across borrowers within those segments, the benefit of diversification would be limited. To evaluate this concentration, we construct a sample of 3,236 BDC-quarters with data on both commitment books and portfolio holdings and separately compute the same concentration measures for these off- and on-balance-sheet exposures.[9] We consider borrower segments at the industry, headquarters-state, and PE-sponsor levels, and use the Herfindahl–Hirschman Index (HHI) and top-three shares as concentration measures.

Table 4 shows that unfunded commitments are substantially more concentrated than the same BDC's portfolio holdings. Specifically, the median HHI is 0.23 versus 0.13 at the industry level, 0.18 versus 0.08 at the headquarters-state level, and 0.16 versus 0.04 at the sponsor level. The same pattern holds when concentration is measured by top-three shares. These differences are statistically significant for all segment levels and concentration measures, indicating that BDCs are exposed to less diversified unfunded commitments than their own on-balance-sheet loan portfolios. Our evidence in the Internet Appendix suggests that this concentration likely reflects information advantages as BDCs selectively extend commitments to borrowers for which they have superior screening or monitoring capacity.[10]

[9] This sample includes all BDC-quarters with data on both commitment books and portfolio holdings for which we have information on the borrower's industry, headquarters state, and PE sponsor from PitchBook.

[10] Internet Appendix Section IA.3 shows that commitment books exhibit strong specialization as they overweight preferred industries, geographies, and sponsors far more than the same BDC's loan portfolio does, and that within a segment, commitments are extended selectively to borrowers with better credit quality, sponsor backing, and equity held by the BDC, consistent with the monitoring roles of PE sponsors

Concentrating commitments in a few borrower segments increases BDC-level volatility if liquidity shocks are correlated across borrowers within a segment. To quantify this correlation, we conduct a variance decomposition by regressing the borrower-quarter liquidity shock on different sets of fixed effects and computing the share of variation explained by each set. Table 5 shows that time fixed effects alone absorb roughly 1% of variation, suggesting that aggregate time variation in the shocks is small. However, industry-by-time and HQ-state-by-time fixed effects absorb 4–10% and 5–12% respectively, consistent with liquidity shocks being correlated among borrowers within the same industry and geography.

We further assess the implications of limited diversification by comparing the BDC-level percentage volatility estimated in Subsection 2.2.1 with a fully diversified benchmark, defined as the volatility of an equal-weighted hypothetical book of all BDCs' commitments. Internet Appendix Table IA.1 shows that the volatility of borrower liquidity shocks experienced by individual BDCs is roughly three times as large as the diversified benchmark. This sizable volatility gap indicates that borrower liquidity shocks diversify only partially within a BDC, exposing BDCs to volatile cashflows through the commitment book.

2.2.3 Undiversifiable Component of Borrower Liquidity Shocks

Even if a BDC's commitment book were perfectly diversified, there may still be a common component in borrower liquidity shocks—beyond the within-segment correlation discussed above—that cannot be diversified away. Figure 3 plots the quarterly averages of borrower liquidity shock measures between 2017Q1 and 2025Q4. A salient event is the 2020Q1 COVID crisis, where borrower drawdown activity spikes: the average reduction in unfunded amounts reaches roughly 25% and the fraction of borrowers drawing cash reaches about 55%. Internet Appendix Figure IA.2 shows that across commitment types, revolvers show a stronger

(Haque, Mayer, and Wang, 2026) and dual debt–equity holders (Davydiuk, Erel, Jiang, and Marchuk, 2025).

COVID-quarter comovement relative to DDTLs. These episodes of synchronized drawdown suggest the existence of commonality in liquidity shocks across borrowers.

BDCs' borrowers are risky middle-market firms, and their liquidity shocks may comove with those of highly leveraged public firms and with market-wide conditions. To examine this commonality, we regress borrower-quarter liquidity shocks on time-series factors measured outside the private credit market. Table 6 reports the estimation results. Panel A uses quarterly average percentage change in credit line drawn balance from S&P Capital IQ to capture the drawdown activity of public firms. We measure this activity separately for four groups of firm by lagged Debt/EBITDA, representing different leverage profiles, with details in Internet Appendix IA.2.2. The estimates suggest that BDC borrowers' liquidity shocks comove with the drawdowns of public firms, especially those with higher leverage or negative earnings. Panel B regresses the shock on market-wide macro and credit factors: changes in the BBB and high-yield credit spreads, the S&P500 return, and changes in the VIX. All estimates suggest that borrowers on commitment books pass correlated liquidity shocks to BDCs when equity and credit markets are under stress.

Taken together, the concentration of commitments (Section 2.2.2) and the commonality of shocks documented here jointly amplify BDC-level liquidity risk. Indeed, Table 5 shows that 7–9% of variation in borrower liquidity shocks remains at the BDC level, suggesting that the residual risk from liquidity provision borne by individual BDCs can be economically significant. The next subsection shows that bank credit lines serve as a backstop for the residual liquidity risk, providing the second layer of insurance in the credit chain.

2.3 Bank Credit Lines as a Liquidity Backstop

Facing volatile cashflows from their commitment books, BDCs may manage this liquidity risk with bank credit lines. In Figure 1, white and green bars plot the aggregate undrawn bank

credit line capacity available to BDCs and their total cash holdings. Bank credit capacity has been growing at a similar scale to BDCs' unfunded commitments to portfolio companies over 2005–2025, whereas cash holdings provide only a smaller additional buffer. The dashed line shows that access to bank credit lines is likewise widespread, with the fraction of BDCs holding one rising to about 90% by 2025.

These credit lines provide an important source of liquidity to BDCs. As Figure 4 shows, the aggregate undrawn fraction of the total bank credit lines has remained at roughly 40–50% over time, which provides a backstop for managing liquidity needs, including drawdowns of unfunded commitments. Indeed, BDCs themselves identify bank credit lines as the primary backstop for their unfunded commitments in regulatory filings.[11] Figure 5 reports the share of BDC 10-K filings naming each liquidity source as backup for unfunded commitments. Bank credit facilities (82.0%) and cash (75.2%) are the most frequently named sources, far ahead of operating cash flow, marketable securities, and LP capital commitments. Moreover, because BDCs must distribute most of their income to maintain tax status, they hold only a small cash buffer.[12] So bank credit lines, rather than cash, are likely the most economically important liquidity source for backing unfunded commitments.

The backstop also operates in flows. Internet Appendix Section IA.5 shows that when a BDC faces greater liquidity needs, it responds on multiple bank credit line margins: per dollar of investment cash outflow, the BDC draws about 10 cents on its existing bank credit lines and adds roughly another 10 cents of committed capacity through limit amendments and newly originated facilities, with no offsetting terminations. Moreover, this backstop is resilient to stress: Internet Appendix Table IA.2 shows no contraction in committed bank credit limits for BDCs more exposed to regional or low-capital banks around the 2023

[11] We classify 1,243 BDC 10-K filings and restrict to the 605 filings that explicitly link a liquidity source to unfunded commitments. Internet Appendix Figure IA.3 reports disclosure status over the full sample.

[12] Internet Appendix Figure IA.4 shows that the ratio of BDCs' undrawn bank credit to cash holdings is several times that of both nonfinancial and financial public firms.

regional bank crisis. Overall, the evidence indicates that BDCs use bank credit lines as the key backstop for providing liquidity insurance to their own borrowers.

3 A Model of Layered Liquidity Provisions

We develop a model of an intermediation chain where a BDC extends credit lines to its borrower firms and a bank extends a credit line to the BDC. Since the BDC can draw on its bank credit line whenever a borrower draws on its own, the stacked commitments may appear to operate as pure pass-through. The model shows otherwise: the optimal contract features *partial insurance*. Because liquidity risk is undiversified at the BDC level, passing every draw through loads the BDC with bank debt precisely in the states where its collections are weakest; with bankruptcy costly, full insurance is not optimal.

3.1 Environment and Agents

There are three dates, $t = 0, 1, 2$, one BDC, and one bank. Motivated by the undiversified borrower liquidity shocks documented in Section 2.2, we keep firms *finite*: we use two firms for illustration and present formal results for n finite firms. All agents are risk neutral. Let $R > 1$ denote the gross market return, the opportunity cost of funds. For simplicity, interest does not compound: a dollar advanced at either $t = 0$ or $t = 1$ owes the same gross rate at $t = 2$, when all debts are due.

Firms. At $t = 0$, each firm raises one dollar to launch a long-term project that, if continued to maturity, produces $y > 1$ at $t = 2$. Then each firm receives internal cash c, used for $t = 0$ transfers such as credit line fees. The residual cash is paid out to shareholders beyond creditors' reach, as in Leland (1994).

At the interim date $t = 1$, with probability $p \in (0, 1)$, firm $i \in \{1, 2\}$ is hit by a

liquidity shock that requires a cash injection ρ_i, drawn uniformly from $[\underline{\rho}, \bar{\rho}]$ with CDF $F(\rho) = \frac{\rho - \underline{\rho}}{\bar{\rho} - \underline{\rho}}$; shocks are independently and identically distributed across firms, and we write $\rho_i = 0$ when no shock occurs. Absent the injection, the project is liquidated and yields zero. To accommodate the lumpiness introduced by finite firms, we allow for partial liquidation. Continuing a fraction $x_i \in [0, 1]$ of the project requires an injection $\rho_i x_i$ and produces $y x_i$. Shocks are verifiable, so a firm cannot misreport one to divert credit. Figure 3.1 summarizes the timeline of a firm's project.

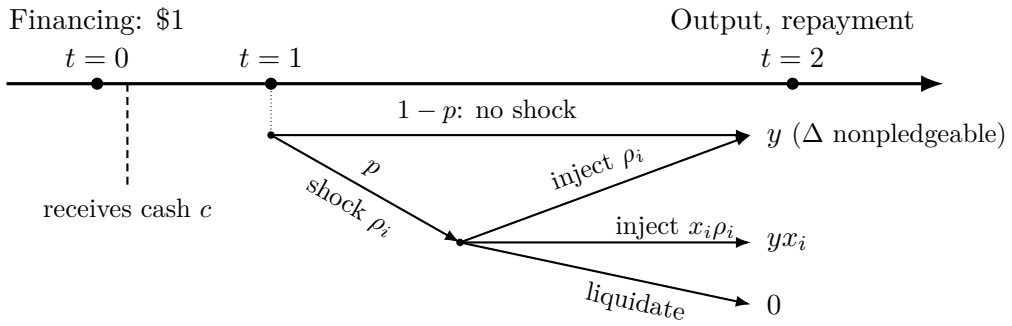


Figure 3.1: Timeline.

Of the output of each continued unit, Δ is nonpledgeable and accrues to the entrepreneur. One microfoundation is moral hazard, under which Δ is the rent the entrepreneur must retain to exert effort.[13] We maintain the following parameter assumptions.

Assumption 1.

$$y - \Delta < R\underline{\rho} < R\bar{\rho} < y. \tag{1}$$

The inequality $R\bar{\rho} < y$ implies that continuing a shocked firm is always socially valuable, as the output y exceeds the cost of even the largest liquidity injection $R\bar{\rho}$. However, a shocked firm cannot raise ρ_i *ex post* at $t = 1$: its pledgeable income $y - \Delta$ falls short of the

[13]Formally: after the shock, the entrepreneur chooses whether to exert effort. With effort the project succeeds at $t = 2$; with shirking it succeeds only with probability $\pi < 1$ but yields a private benefit B. Inducing effort requires retaining at least $\Delta \equiv \frac{B}{1-\pi}$, leaving $y - \Delta$ pledgeable to outside creditors.

repayment $R\underline{\rho}$ owed on even the smallest injection. Liquidity must therefore be arranged in advance.

Credit lines are a classic form of liquidity insurance offered by intermediaries (Holmström and Tirole, 1998). An intermediary commits to lend up to a prespecified limit, against which a firm can draw cash when a shock hits. Diversification across firms allows the intermediary to fund the draws of shocked firms through a cross-subsidy from unshocked firms, which do not draw. The pooling explains why self-insurance through cash is inefficient: with probability $1-p$ the shock does not hit and the precautionary buffer sits idle, forgoing the market return R. The following condition ensures that a firm can afford the credit line fee and does not self-insure through the cash paid out to its shareholders (Lemma A.1 in Appendix A.2).[14]

Assumption 2.

$$\Delta < R\underline{\rho}, \qquad \frac{p\Delta}{R} \leq c < \underline{\rho}. \tag{2}$$

We introduce a binary bankruptcy cost, incurred whenever a borrower defaults on its debt; for a firm, this loss is $\lambda > 0$. Firm defaults coincide with liquidity shocks regardless of the exact debt contract: a shocked firm's pledgeable income falls short of the cost of liquidity injection, $R\rho_i$ (Assumption 1), while an unshocked firm repays in full. The expected total firm bankruptcy loss is therefore a constant $2p\lambda$.

Credit chain and BDC. Motivated by the evidence that a BDC's commitment book is concentrated (Section 2.2) and that BDCs rely on bank credit lines (Section 2.3), we study liquidity provision under *imperfectly diversified liquidity risk* through a *credit chain*—firms obtain funding from BDCs, and BDCs in turn from the bank. Because the BDC can draw

[14]The cash cannot restore a shocked firm's solvency, so an injected dollar earns only the continuation rent $\frac{\Delta}{\rho_i}$, below the market return R by $\Delta < R\underline{\rho}$; shareholders therefore do not inject at $t = 1$.

on its bank credit line whenever a borrower draws on its own, the chain may appear to be a pure pass-through. The model shows that this need not be the case, due to a BDC-level friction.

At $t = 0$, the BDC extends to each firm a term loan of size 1 and a credit line with limit ℓ, both at a gross rate R_N (N for Nonbank), and charges a credit-line fee ϕ_N, which the firm pays at $t = 0$ from its cash c. The borrower firms' shocks, (ρ_1, ρ_2), then determine the BDC's liquidity needs.

To fund its borrowers, the BDC obtains from the bank at $t = 0$ a term loan of size 2 and a credit line with limit L, both at the market gross rate R, and pays a fee ϕ_B (B for Bank). We assume that BDC shareholders net the fees, so the BDC carries no cash after $t = 0$: it distributes the surplus $2\phi_N - \phi_B$ to its shareholders, as in Leland (1994), or collects the shortfall from them. These assumptions keep the determination of the BDC's default clean: its debt to the bank reflects only what it draws, any contract-dependent payoff to the bank is absorbed by the fee ϕ_B, and no residual cash remains to avoid default. The bankruptcy cost—our key friction—therefore depends only on the credit limits, the extent of liquidity insurance that the model addresses. Note that BDC shareholders indeed have no incentive to inject funds ex post: cash is needed exactly in the states where the BDC is insolvent.

Depending on the liquidity injection, a fraction $x_i \in [0, 1]$ of firm i's project is continued. A firm's draw is capped by its own credit limit, $\rho_i x_i \leq \ell$, and the BDC can fund total draws only up to the bank credit limit, $\sum_{\rho_i > 0} \rho_i x_i \leq L$. Since credit lines are commitments, the choice of $\{x_i\}$ matters only when one of these credit limits binds, and the BDC cannot restrict draws otherwise. Hence, when only one firm is shocked, the continued fraction is $x_i = \min\left\{1, \frac{\ell}{\rho_i}, \frac{L}{\rho_i}\right\}$. When both firms are shocked, the continuation rule is *smallest-shock-first*: each continued unit yields the same output but requires an injection equal to the firm's shock, so the BDC prioritizes the firm with the smaller shock. That is, if $0 < \rho_1 \leq \rho_2$, firm

2 draws only out of the liquidity left after firm 1's draw, $L - \rho_1 x_1$:

$$\begin{aligned} x_1 &= \min\left\{1, \frac{\ell}{\rho_1}, \frac{L}{\rho_1}\right\}, \\ x_2 &= \min\left\{1, \frac{\ell}{\rho_2}, \frac{\max\{L - \rho_1 x_1, 0\}}{\rho_2}\right\}. \end{aligned} \tag{3}$$

This is consistent with credit line covenants in practice, under which a firm's drawdown can be rationed when its financials deteriorate. We abstract from any penalty on the BDC when its bank credit limit binds and firms cannot draw in full. Such a penalty can be added as long as it is sufficiently small relative to the bankruptcy cost; this is reasonable because default on bank debt destroys franchise value for both the BDC and its manager's other funds.

To summarize, we denote by $\mathcal{C}$ the contracts along the credit chain,

$$\mathcal{C} = \Big(\ell,\, R_N,\, \phi_N;\; L,\, \phi_B;\; \{x_i\}\Big), \tag{4}$$

which includes the firm credit line limit ℓ, rate R_N, and fee ϕ_N; the bank credit line limit L and fee ϕ_B; and the continuation rule $\{x_i\}$, which is smallest-shock-first, as in (3), at the optimum (formally shown in Lemma A.2 in Appendix A.2).

We now characterize the BDC's bankruptcy cost and its payoff. Default occurs at $t = 2$, when repayments are due (although uncertainty resolves at $t = 1$ with the realized shocks). An unshocked firm repays R_N. A shocked firm continued at fraction x_i owes $R_N(1 + \rho_i x_i)$ on its term loan and draw. Since each continued unit's pledgeable income $y - \Delta$ already falls short of the repayment $R_N \rho_i$ on the drawn credit line (Assumption 1 and $R_N \geq R$), the firm defaults and repays its entire pledgeable income $(y - \Delta)x_i$. The BDC owes the bank $R\,(2 + \sum_i \rho_i x_i)$. Its net worth at $t = 2$ is therefore

$$\Pi(\rho_1, \rho_2; \mathcal{C}) = \sum_{i=1}^{2} \Big[R_N \mathbf{1}\{\rho_i = 0\} + (y - \Delta) x_i\, \mathbf{1}\{\rho_i > 0\}\Big] - R\Big(2 + \sum_{i=1}^{2} \rho_i x_i\Big). \tag{5}$$

The BDC defaults when $\Pi < 0$; its insolvency entails the binary deadweight loss 2λ (scaled to the two-firm book), and the bank recovers the BDC's collections from firms. The BDC's expected payoff, expressed in $t = 2$ value, is then

$$V(\mathcal{C}) \;=\; R\,(2\phi_N - \phi_B) + \mathbb{E}\Big[\max\{\Pi, 0\}\Big] - 2\lambda\,\Pr(\Pi < 0), \tag{6}$$

the fee income net of the bank fee, plus the expected loan income under limited liability, less the expected bankruptcy cost.

The BDC's default friction—arising from its undiversified commitment book and, as a nonbank, its lack of a public liquidity backstop—distinguishes its liquidity provision from a bank's. In essence, the difference lies in the order of diversification and default realization: under direct bank lending, borrower liquidity risk is fully diversified on the bank's large balance sheet, whereas in the credit chain, default cost is incurred first at the BDC level, before residual risk is pooled upstream by the bank (Jensen's inequality).

Bank. Our paper takes as given that the credit chain arises from regulatory arbitrage and studies liquidity provision along the chain. In practice, a bank's direct loan to a middle-market firm carries a higher capital charge than an indirect loan through a nonbank financial institution (NBFI) such as a BDC (Chernenko, Ialenti, and Scharfstein, 2025). This is because of an NBFI's equity buffer and *diversification*: direct loans incur capital charges obligor by obligor, whereas the NBFI, itself a loan portfolio, is a market solution that captures the diversification benefit (Huang and Jiang, 2026).

We take these regulatory costs as exogenous and summarize them as a per-dollar wedge: funding a firm directly costs $R + \kappa$, while lending to a BDC costs R, its regulatory cost normalized to zero.

The bank operates in a competitive market. Its large, well-diversified book provides

ample funding relative to the BDC and its borrower firms. It therefore prices the facility to the BDC ex ante, breaking even in expectation rather than state by state. By pooling the BDC with its other portfolio firms, the bank provides a second layer of liquidity insurance. At $t = 2$, given the realized firm shocks (ρ_1, ρ_2), the bank collects from the BDC,

$$R\Big(2 + \sum_{i=1}^{2} \rho_i x_i\Big) + \min\{\Pi, 0\}, \tag{7}$$

where the first term is the face value paid in full if the BDC remains solvent, i.e., R accrued on the term loan and the draws, and the second term is the shortfall when the BDC defaults, in which case the bank recovers only the BDC's collections from its borrower firms. The bank participates if the $t = 0$ fee ϕ_B at least covers the expected credit loss:

$$R\,\phi_B \geq \mathbb{E}\Big[\max\Big\{-\Pi(\rho_1, \rho_2; \mathcal{C}),\, 0\Big\}\Big]. \qquad \text{(Bank PC)} \tag{8}$$

As discussed above, compensating the bank's credit loss through the fee, in place of a default premium in the bank rate, keeps the BDC's face value, and hence its default, determined by the credit line limits alone.

3.2 Direct Bank Lending

We begin with a benchmark in which the bank lends directly to the two firms, extending to each a term loan of size 1 and a credit line. We maintain the following assumption, under which the firms' pledgeable income covers the expected cost of their funding:

Assumption 3.

$$y - \Delta \;\geq\; R\,(1 + p\,\mathbb{E}[\rho_i \mid \rho_i > 0])\,. \tag{9}$$

Under this condition, and absent a regulatory capital cost ($\kappa = 0$), direct lending attains

the first best. Because continuing a shocked firm is socially optimal under Assumption 1, which gives $y - R\rho_i > 0$, the first best fully insures all liquidity shocks. The bank's large book provides ample funding relative to the two firms, so it needs to break even only in expectation across states, and Assumption 3 guarantees that granting each firm a credit line limit of $\bar{\rho}$, under which every shocked firm continues in full, is feasible.

Because bank lending to the BDC carries no regulatory cost, Assumption 3 also ensures that the bank's participation constraint does not restrict liquidity insurance provision in the credit chain.

A positive regulatory capital cost κ reduces the direct-lending surplus through two channels: the funding cost increases,[15] and, once the bank passes it through to a rate approaching the pledgeable amount $y - \Delta$, full insurance is no longer feasible. The direct-lending surplus then falls short of what lending through BDCs attains at the lower regulatory cost, and for κ sufficiently large, a planner constrained by the same regulation would select the credit chain. We characterize its constrained-efficient allocation next.

3.3 Credit Chain

Because the credit chain is a credit line on a credit line, one might think it operates as a pure pass-through: the BDC draws on its bank credit line whenever a borrower firm draws, and adding this middle layer should preserve the full-insurance allocation of direct lending with $\kappa = 0$. We show that partial insurance arises instead. Our model introduces a contracting friction to the liquidity provision of Holmström and Tirole (1998). As the insurer, the BDC is exposed to *undiversified liquidity risk* and relies on bank debt, so providing more insurance raises its own default probability. With bankruptcy costs, full insurance is no longer optimal.

[15] The benefit of capital regulation is beyond the scope of this paper.

3.3.1 The Contracting Problem

To study the optimal insurance, we assume that the BDC has all bargaining power and proposes the loan and credit line contracts to the firms and to the bank, with $t = 0$ transfers through the credit line fees. Bargaining power lets the BDC extract the most from firms to repay its bank debt and avoid bankruptcy. The fee paid to the bank, ϕ_B, keeps the bank rate fixed at R, so that compensating the bank for credit risk does not change the BDC's face value and thereby its bankruptcy risk. The fee collected from firms, ϕ_N, is needed because firms prefer more insurance than the BDC does due to the nonpledgeable rent, and the fee payment aligns the BDC's incentive to provide the optimal insurance. Since the expected firm bankruptcy cost is also a constant, the BDC's optimal contract achieves the *constrained-efficient allocation* within the contract class $\mathcal{C}$ in (4); Lemma A.4 in Appendix A.2 formally shows this alignment.

Specifically, the BDC makes a take-it-or-leave-it offer of the contract $\mathcal{C}$ in (4): the firm credit line terms (ℓ, R_N, ϕ_N), the bank credit line terms (L, ϕ_B), and the continuation rule $\{x_i\}$. The BDC solves

$$\max_{\mathcal{C}} \; V(\mathcal{C}) \;=\; R\,(2\phi_N - \phi_B) + \mathbb{E}\Big[\max\{\Pi(\rho_1, \rho_2; \mathcal{C}), 0\}\Big] - 2\lambda \Pr\Big(\Pi(\rho_1, \rho_2; \mathcal{C}) < 0\Big) \tag{10}$$

$$\text{s.t.} \quad R\,\phi_B \geq \mathbb{E}\Big[\max\{-\Pi(\rho_1, \rho_2; \mathcal{C}), 0\}\Big] \tag{Bank PC}$$

$$R\,\phi_N \leq (1-p)(y - R_N) + p\,\Delta\,\mathbb{E}\Big[x_i \mid \rho_i > 0\Big] - (1-p)\Delta \tag{Firm PC}$$

$$\rho_i x_i \leq \ell, \quad \sum_{\rho_i > 0} \rho_i x_i \leq L \tag{Credit Limits}$$

where $\Pi(\rho_1, \rho_2; \mathcal{C})$ is the BDC's net worth at $t = 2$ in (5). The BDC chooses the optimal contract within the contract space $\mathcal{C}$ in (4) subject to three sets of constraints: the bank's participation constraint to break even restates (8); the firm's participation constraint requires

the insurance to beat the uninsured outside option of a term loan only, which gives $(1-p)\Delta$ because the firm is then liquidated whenever shocked;[16] finally, drawdowns satisfy both the individual firm credit line limits and the BDC's bank credit limit. As noted in Section 3.1, credit lines are commitments, so the continuation rule $\{x_i\}$ matters only when one of these credit limits binds, and the optimal rule is the smallest-shock-first allocation (3).

Pricing. We now derive the optimal pricing and reduce the contracting problem to the choice of credit limits (ℓ, L), with continuation $\{x_i\}$ determined by (3). First, both participation constraints bind, as the BDC extracts all surplus. Second, the BDC prefers loan repayment at $t = 2$ rather than fee income at $t = 0$, as the former strengthens its net worth against default. It therefore charges the highest rate at the firm's pledgeable income, $R_N^* = y - \Delta$. It follows that

$$R\phi_N^* = p\,\Delta\,\mathbb{E}\Big[x_i \mid \rho_i > 0\Big]: \tag{11}$$

the insurance premium exactly extracts the entrepreneur's nonpledgeable benefit from the projects continued under the insurance. Appendix A.2 formally establishes these results.

With these results, the contracting problem reduces to the following.

$$\max_{\ell, L}\; V\Big(\ell, L, R_N^*, \phi_N^*, \phi_B^*\Big) \;=\; \underbrace{\mathbb{E}\Big[\sum_{\rho_i>0}(y - R\rho_i)\,x_i\Big]}_{\text{continuation surplus}} \;-\; \underbrace{2\lambda\,\Pr\Big(\Pi(\rho_1,\rho_2;\ell,L)<0\Big)}_{\text{bankruptcy cost}} + \text{constant}$$
$$\text{s.t.}\quad \{x_i\} \text{ in (3)}. \tag{12}$$

The BDC chooses the optimal credit line limits, ℓ committed to the firm and L on the bank credit line, to trade off the surplus of more continued projects under insurance, against its

[16] Here we assume that the lender has all the bargaining power also without insurance. This is without loss of generality: the outside option enters only as a level shift and does not affect the contract choice.

bankruptcy cost that the insurance incurs.

Remark 1 (Contract space)**.** Our contract space is restricted to term loans and credit lines, consistent with the financing arrangements documented in Section 2. Under direct lending (Section 3.2), the restriction is without loss: liquidity risk is perfectly diversified, and a credit line implements the constrained-efficient allocation as in Holmström and Tirole (1998). However, in the credit chain, it is with loss as the debt contract prevents the bank from transferring resources to a bankrupt BDC to avoid the deadweight loss (for example, through state-contingent debt relief). We argue that such transfers face a commitment problem: ex post, the bank has little incentive to inject resources into an already bankrupt BDC. Bank debt is also the empirically relevant contract space.

3.3.2 Partial Insurance

We first present the formal results for a general book of $n \geq 2$ firms, and then use the two-firm example to illustrate the economics.

Proposition 1 (Optimal insurance)**.** *Under Assumptions 1–3:*

(i) If $\lambda = 0$, the first best of full insurance is achieved, with $\ell^* = \bar{\rho}$ and $L^* = n\bar{\rho}$;

(ii) Suppose there is diversification benefit at the BDC, $n(y - \Delta) > R(n + \bar{\rho})$ and shock probability is small $p < \hat{p}$. If bankruptcy is sufficiently costly, $\lambda > \hat{\lambda}$, the optimal contract features partial insurance: a full firm credit line, $\ell^* = \bar{\rho}$, and a partial bank credit line, $L^* < n\ell^*$. The thresholds $\hat{p}$ and $\hat{\lambda}$ are presented in Appendix A.2.

Without the bankruptcy cost, the credit chain achieves the first best, as can be seen from (12): with $\lambda = 0$, the BDC chooses the contract that maximizes continuation and all shocked firms are continued. Intuitively, adding a frictionless middle layer to direct lending

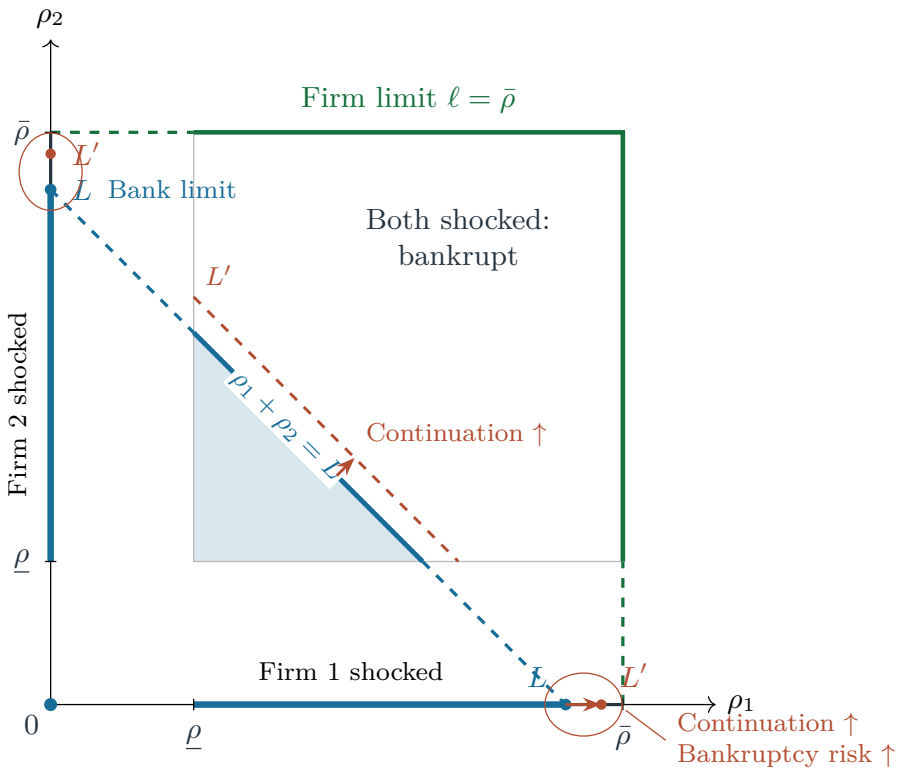


Figure 3.2: Credit Line Limits.

(Section 3.2) should preserve its first best outcome. The result also aligns with Holmström and Tirole (1998): with a fixed investment scale here, insurance optimally covers shocks up to the first-best threshold.

With bankruptcy frictions, the firm credit line is full at the first best threshold, $\ell^* = \bar{\rho}$, and the bank credit line is partial, $L^* < n\bar{\rho}$; together they lead to partial insurance. Figure 3.2 illustrates this in the two-firm example. It plots the support of the two firms' shock realizations: since the no-shock realization is an atom, the dot marks the state with no shocks, the two segments mark the states where only one firm is shocked, and the square marks the states where both are shocked. The green lines, $\ell = \bar{\rho}$, mark the full firm credit limit. The line $\rho_1 + \rho_2 = L$ shows where the bank credit limit allows full draws. The blue-

shaded states, to the lower left of both limits, are those where all draws are funded in full without partial liquidation.

We first fix the firm credit limit at the first best threshold, $\ell = \overline{\rho}$, and explain our key result of partial insurance, $L^* < 2\overline{\rho}$. The BDC book provides the first layer of insurance: injecting liquidity into a shocked firm is costly ex post, but in the one-shock states, diversification allows the BDC to subsidize the shocked firm with the pledgeable income of the unshocked firm. This layer, however, runs out when both firms are shocked or when a lone shock is large, and the BDC itself is at a loss. The bank credit line provides the second layer of insurance, pooling across the BDC's own states: draws in its loss states are subsidized by its profitable states. Bankruptcy costs, however, make the BDC cautious about providing insurance in exactly those loss states and therefore choose underinsurance ex ante.

To see the marginal trade-off, the first-order condition with respect to L is

$$\mathbb{E}\left[\sum_{\rho_i>0}(y - R\rho_i)\frac{\partial x_i(\ell, L)}{\partial L}\right] = 2\lambda\frac{\partial \Pr(\Pi < 0)}{\partial L}. \tag{13}$$

The left side is the insurance benefit of a marginal dollar of committed funding that continues the marginal firm in the shocked states. In Figure 3.2, an increase of L to L' covers more shock states in full and reduces partial liquidation of the marginal firm. The right side of (13) is the marginal bankruptcy cost. The extra bank credit weakens the BDC precisely in the states where the lines it issues to firms are drawn. Because the bankruptcy cost is binary, states already in default add no further loss; in the figure, these are the two-shock states in the square. The marginal states are the one-shock states, where the BDC trades off more insurance that continues a larger shock against a higher probability of bankruptcy.

Last, to contain the BDC's debt that its insurance provision loads on, a small bank credit limit is more favorable than a small firm limit, as it allows for more diversification

benefit. States away from the 45-degree line are better diversified, for example, the one-shock states. A rationed bank credit limit permits draws in exactly these states and thus preserves more diversification, whereas a reduction in the firm limit rations firm shock sizes uniformly, regardless of the other firm's shock realization, forgoing the diversification benefit of covering a large, lone shock.

Remark 2 (Connection to literature)**.** Our partial insurance result echoes the optimal coverage in Holmström and Tirole (1998), which lies between the first-best shock threshold and the pledgeable shock threshold as the planner trades off continuing more shocks against scaling up investment. Here, insurance is negative NPV for the provider when the pledgeable-income buffer from unshocked firms falls short and draws trigger BDC default, so there is also a counterforce that cuts insurance, containing draws in the poorly diversified realizations with smaller pledgeable income at the BDC. Our model also speaks to Diamond (1984), where adding an intermediary is beneficial under diversification. When liquidity shocks are not perfectly diversified and the intermediary incurs a deadweight loss, direct lending that removes the middle layer would be better off (absent the regulatory cost).

3.4 Model Extensions

In this part, an implication of the partial insurance in the credit chain is that firms sharing the same constrained liquidity pool inefficiently shirk in liquidity management due to the externality in the spirit of the tragedy of the commons (Hardin, 1968). Second, we relax the assumption of purely idiosyncratic liquidity shocks by allowing an aggregate component.

3.4.1 Firm Liquidity Management in the Credit Chain

The market implementation—layered credit lines—carries a further implication. The bank credit line is a common liquidity pool that the BDC's borrower firms share, and when

$0 < L^* < n\ell^*$ the pool is constrained, leading to an externality in firms' liquidity management choices a la tragedy of the commons (Hardin, 1968). An individual firm weighs the cost of liquidity management against its own expected coverage; it ignores that, because the shared liquidity pool is constrained, its exposure crowds out the coverage of every other firm sharing the pool. Hence, each firm's liquidity management choice has an externality on the others. Specifically, the individual's optimization neglects the following crowding-out wedge in the planner's problem, where $\mathbb{E}[x_j \mid \rho_j > 0]$ is the expected continuation fraction of shocked firm j. Because of this wedge, equilibrium effort in liquidity management is inefficiently low: Proposition 2 in Appendix A.4 shows that firms shirk in liquidity management relative to the planner's choice, $p^{eq} > p^{planner}$, when coverage is partial ($0 < L^* < n\ell^*$), while the two choices coincide under full coverage ($L^* = n\ell^*$).

The externality is therefore specific to liquidity provision by nonbanks, whose constrained coverage arises from concentrated portfolios and insolvency costs absent a government backstop. In contrast, bank credit lines provide full coverage ($L^* = n\ell^*$) and the externality vanishes.

The liquidity pool echoes the simultaneous drawdowns of committed bank lines studied by Bräuning and Ivashina (2026), in which firms draw on their facilities at once and strain lender capacity. The difference is that theirs is an ex-post run, whereas ours is an ex-ante distortion in firms' liquidity management.[17]

3.4.2 Aggregate Liquidity Risk

We introduce aggregate liquidity risk by letting the shock probability depend on a common state Z. Conditional on Z, firm shocks remain independent, each occurring with probability

[17] The run channel is absent in our model because of timing: drawdowns occur only after liquidity shocks (which are verifiable) are realized, so an unshocked firm gains nothing from drawing and must still repay interest.

p_Z.

Risk-neutral pricing absorbs idiosyncratic risk at the bank, but its total drawdowns and collections still vary with Z—aggregate liquidity risk remains on the bank balance sheet. Specifically, let $\pi_B(Z; L)$ denote the bank's net revenue in state Z: the fee ϕ_B plus its expected credit shortfall on the BDC under the physical distribution $\mathbb{P}$.

Aggregate risk affects the bank's funding layer, as its investors' risk-adjusted pricing kernel enters the bank's participation constraint. Suppose first that the bank relies on wholesale funding, supplied by rational investors who reprice the bank's cash flows with market conditions; this corresponds to the investors in Holmström and Tirole (1998), who require the bank to break even state by state, the state here being Z. Let $M(Z)$ denote bank investors' marginal value; the bank's cash flows must then break even from these investors' perspective:

$$\mathbb{E}[M(Z)\,\pi_B(Z; L)] = 0 \quad \Longleftrightarrow \quad \mathbb{E}^{\mathbb{Q}}[\pi_B(Z; L)] = 0. \tag{14}$$

In an aggregate high-draw state, many borrowers draw simultaneously and bank collections deteriorate precisely when investors' marginal utility is high, requiring greater compensation to support a given capacity. Wholesale funding thus makes aggregate liquidity insurance expensive when it is most valuable and, as aggregate risk grows, potentially unviable.

Funding from the bank's deposit franchise, however, requires no such premium (Drechsler, Savov, and Schnabl, 2021). Depositors value banking services and FDIC insurance rather than state-contingent returns; we therefore model deposit funding, in reduced form, as risk neutral, and the Bank PC holds under the physical measure,

$$\mathbb{E}^{\mathbb{P}}[\pi_B(Z; L)] = 0. \tag{15}$$

This also reflects the stickiness of deposits, whose supply is not perfectly correlated with aggregate drawdowns, giving banks a special advantage in providing liquidity insurance (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006).

Therefore, insurance against aggregate liquidity risk is supplied by the private sector only to the extent of a deposit franchise partly supported by public backstops. The chain ultimately reallocates aggregate draw risk to the bank's funding stakeholders and, in the tail, to the depositors.

4 Evidence on Model Implications

The model yields two implications that we take to the data. First, the BDC may choose undrawn bank credit capacity that is insufficient to always fulfill the commitments extended to its borrowers ($L^* < n\ell^*$): liquidity insurance is optimally *partial* when bankruptcy risk is sufficiently costly. Second, partial insurance implies *ex-post rationing*: in states where realized borrower liquidity shocks exceed the BDC's bank credit capacity ($\sum_{\rho_i>0} \min\{\rho_i, \ell^*\} > L^*$), the BDC cannot accommodate all drawdown requests. Borrower drawdowns are therefore rationed when widespread liquidity needs hit a BDC whose liquidity backstop is relatively small for its unfunded commitments. This section tests the two implications in turn.

4.1 Partial Liquidity Insurance

We first examine the relationship between the commitments a BDC extends to its borrowers and those it receives from banks. Because BDCs use bank credit lines also for other liquidity needs (Internet Appendix Section IA.5), the level of undrawn credit may not measure the liquidity preserved for commitment books. We therefore estimate the liquidity backstop by regressing a BDC's undrawn bank credit on its total unfunded commitments, controlling for

the BDC's size (lagged total assets) and leverage (total debt divided by total assets). We also control for a dummy for the BDC's listing status, which may influence its financing choices. The regressions include fixed effects at the year-quarter and the BDC levels. The coefficient on total commitments thus captures the association between the liquidity the BDC extends and receives, and is not confounded by time-invariant BDC heterogeneities or macro shocks.

Panel A of Table 7 reports the estimation results. Column 1, where the dependent variable is the BDC's total undrawn bank credit, scaled by lagged total assets, provides the closest empirical counterpart to our model's prediction. The coefficient on total unfunded commitments is 0.448 and statistically significant, suggesting that a one-dollar increase in unfunded commitments is associated with about 45 cents of additional undrawn bank credit. In Column 2, we broaden the analysis beyond the model's focus on bank credit by including cash holdings in the dependent variable. The coefficient rises to 0.607. Both coefficients are positive and statistically significant, and both are significantly below one in our F tests.

Our preferred interpretation is that the estimated coefficients in Panel A capture the average liquidity backstop for BDC unfunded commitments. This interpretation requires that, conditional on the controls and fixed effects, other determinants of the BDC's available liquidity do not systematically correlate with its total unfunded commitments.

Under this interpretation, we use the estimated coefficients to calibrate a dollar-valued measure of liquidity backstop and assess its adequacy relative to potential borrower drawdowns at the BDC level. The finding that liquidity backstop increases less than one-for-one with unfunded commitments does not by itself establish partial insurance. Because borrowers need not draw all commitments simultaneously, whether the estimated backstop provides partial coverage for the unfudned commitments depends on the magnitude of BDC-level exposures to borrower liquidity shocks. We therefore compare the dollar-valued volatility of BDC-level liquidity shocks $\widehat{\sigma}^{\$}_{\ell t}$, estimated in Table 3, with the BDC's estimated liquidity

backstop $\widehat{\beta} \times$ Total Unfunded$_{\ell,t-1}$, using the coefficient $\widehat{\beta}$ from Panel A.

Panel B of Table 7 reports the fraction of BDC-quarters where a hypothetical BDC-level liquidity shock would exceed the estimated liquidity backstop. We find that a one-standard-deviation shock would not exceed the estimated backstop in any observation, which is unsurprising because partial insurance is relevant mainly for tail states. By contrast, a two-standard-deviation shock would exceed the backstop in 6.3% of BDC-quarters for undrawn bank credit and 3.6% of BDC-quarters when cash is included. For a three-standard-deviation shock, these fractions rise to 18.2% and 9.0%. Under the maintained interpretation, these results suggest that larger shocks would exhaust the estimated liquidity backstop for a substantial share of observations and are consistent with partial liquidity insurance.

Our interpretation has two limitations. First, other uses of bank credit may correlate with unfunded commitments even after conditioning on the controls and fixed effects. If this correlation is positive, the estimated backstop would be overstated, making the partial-insurance interpretation conservative. Second, a BDC might have access to liquidity sources beyond bank credit lines and cash holdings.[18] These sources may influence both the BDC's bank credit limits and its unfunded commitments, potentially biasing the estimated relationship. They may also provide additional liquidity for borrower drawdowns that our model and empirical analysis do not capture. Although we cannot fully account for these other liquidity sources, the next subsection provides further evidence consistent with partial insurance by examining realized drawdowns.

[18]Internet Appendix Section IA.6 examines uncalled investor capital commitments ("dry powder") and shows that our results remain similar when excluding BDC-quarters that have dry powder.

4.2 Rationing of Borrower Drawdowns

The model's second implication is ex-post rationing: when many borrowers request liquidity at once, a BDC with insufficient liquidity relative to its commitment book cannot accommodate every drawdown request. We test this implication using data on unfunded commitments at the BDC–borrower–quarter level. The ideal test would compare each borrower's drawdown request with the amount it actually receives from the BDC, conditional on whether the total volume of requests the BDC receives ($\sum_{\rho_i>0} \min\{\rho_i, \ell^*\}$) exceeds the liquidity it has (L^*). However, drawdown requests are unobservable. We therefore detect rationing by estimating the sensitivity of realized drawdowns to a proxy for borrower liquidity needs and evaluating how this sensitivity varies with the BDC's liquidity condition. The model implies that borrowers of BDCs with tighter liquidity conditions draw disproportionately less due to the BDC's inability to accommodate all requests.

We measure the borrower's realized drawdown as the decrease in its unfunded commitment, $-\%\Delta Unfunded$, as in Section 2.2. Motivated by facts in Section 2.2.3, we proxy for a borrower's liquidity need with *Industry Peer Drawdown*, defined as the positive part of average credit line drawdown by public firms in a borrower's Fama–French industry that have high leverage (lagged Debt/EBITDA of at least four). This proxy captures variation in the borrower's liquidity needs associated with aggregate and industry-specific shocks.[19] We measure the BDC's *Liquidity Tightness* as the ratio of its total unfunded commitments to the sum of its cash and undrawn bank credit. A higher ratio indicates greater potential drawdown requests relative to available liquidity, hence variation in this ratio captures the BDC's ability to accommodate borrower drawdowns.[20]

[19] Our approach relates to Chodorow-Reich, Darmouni, Luck, and Plosser (2022), who examine how the sensitivity of borrower drawdowns to industry-level liquidity shocks varies across firm sizes. We examine how this sensitivity varies with the nonbank lender's own liquidity condition.

[20] BDCs hold cash and undrawn bank credit for various liquidity needs, so this ratio does not measure the liquidity reserved for unfunded commitments. Our test in this subsection uses variation in the ratio across

To test the implication, we regress the borrower's realized drawdown on the interaction of Industry Peer Drawdown and the BDC's Liquidity Tightness. The model predicts a negative coefficient on the interaction — a lower sensitivity of borrower drawdown to liquidity needs when the BDC itself faces weak liquidity conditions. The regressions include BDC–borrower fixed effects to absorb time-invariant drawdown patterns, BDC-time fixed effects to remove the average drawdown of the BDC's borrowers in a quarter, and industry-time fixed effects to account for average industry drawdowns. Thus, identification comes from comparing the sensitivity of realized borrower drawdowns to industry peers' drawdowns across BDCs with different liquidity conditions. We weight the facility-level observations by lagged unfunded commitment amount to ensure the estimation reflects dollar-valued liquidity needs.

Table 8 reports the results. In column 1, the interaction of Industry Peer Drawdown with the continuous Liquidity Tightness is negative and significant: borrower drawdowns of BDCs with tighter liquidity conditions become less sensitive to their industry peers' drawdowns. Columns 2–4 replace the continuous BDC Liquidity Tightness with indicators for tightness exceeding 100%, 120%, and 150%, respectively. The point estimates' magnitude increases with the severity of tightness: a one-standard-deviation increase in peer drawdowns is associated with 2.7, 4.0, and 5.8 percentage points less drawdown for borrowers of BDCs above the three thresholds. Columns 5 and 6 decompose the drawdown measure, net change in unfunded commitment, into its decrease and increase components. Supporting our interpretation, the result is concentrated on decreases in unfunded amount, whereas increases show no significant response. Overall, borrowers of BDCs with tighter liquidity conditions exhibit a weaker drawdown response to liquidity needs, consistent with ex-post rationing under partial liquidity insurance.

BDCs and time to capture the differences in BDC liquidity conditions and to examine how these differences affect the response of realized borrower drawdowns to liquidity needs.

5 Conclusion

As credit extension migrates from banks to nonbanks, a basic question is where the boundary of banking lies—what banks can do that nonbanks cannot. Liquidity insurance, the commitment to advance cash when a borrower is hit by a shock, has long been the province of deposit-funded banks. We document a new and economically important fact: business development companies (BDCs), as nonbank lenders, now supply it on a significant scale. We establish two empirical patterns in addition to the rapid growth of BDCs' credit commitments during recent years. First, BDCs' commitment books are concentrated and their borrowers' drawdowns are correlated, leaving undiversified liquidity risks at the BDC level. Second, BDCs manage this residual risk with credit lines from banks as a liquidity backstop.

We rationalize these patterns with a model of a credit chain in which liquidity insurance is provided in two layers. The BDC forms the first layer, partially pooling the idiosyncratic shocks of its borrower firms; the bank forms the second, committing liquidity to the BDC against the undiversified risk that remains. The model delivers two implications unique to nonbank liquidity provision. First, because of its undiversified borrower liquidity shocks and its lack of a public backstop, the BDC may optimally provide only partial liquidity insurance. Second, this limited coverage leads to ex-post rationing when borrower liquidity needs exceed the BDC's available liquidity. Our evidence is consistent with both implications.

References

Acharya, Viral V., Heitor Almeida, and Murillo Campello, 2013, Aggregate risk and the choice between cash and lines of credit, *The Journal of Finance* 68, 2059–2116.

Acharya, Viral V., Heitor Almeida, Filippo Ippolito, and Ander Perez-Orive, 2014, Credit lines as monitored liquidity insurance: Theory and evidence, *Journal of Financial Economics* 112, 287–319.

Acharya, Viral V., Nicola Cetorelli, and Bruce Tuckman, 2026, Where do banks end and NBFIs begin?, *The Review of Corporate Finance Studies* 15, 627–659.

Acharya, Viral V., Robert F. Engle, Maximilian Jager, and Sascha Steffen, 2024, Why did bank stocks crash during COVID-19?, *The Review of Financial Studies* 37, 2627–2684.

Acharya, Viral V., Manasa Gopal, Maximilian Jager, and Sascha Steffen, 2025, Shadow always touches the feet: Implications of bank credit lines to non-bank financial intermediaries, Working Paper 33590 National Bureau of Economic Research.

Acharya, Viral V., and Nada Mora, 2015, A crisis of banks as liquidity providers, *The Journal of Finance* 70, 1–43.

Berlin, Mitchell, Greg Nini, and Edison G. Yu, 2020, Concentration of control rights in leveraged loan syndicates, *Journal of Financial Economics* 137, 249–271.

Blickle, Kristian, Cecilia Parlatore, and Anthony Saunders, 2026, Specialization in banking, *The Journal of Finance* 81, 1531–1572.

Block, Joern, Young Soo Jang, Steven N. Kaplan, and Anna Schulze, 2024, A survey of private debt funds, *The Review of Corporate Finance Studies* 13, 335–383.

Bord, Vitaly M., and João A. C. Santos, 2012, The rise of the originate-to-distribute model and the role of banks in financial intermediation, *Federal Reserve Bank of New York Economic Policy Review* 18, 21–34.

Bräuning, Falk, and Victoria Ivashina, 2026, Bank runs and interest rates: A revolving lines perspective, Working Paper 34879 National Bureau of Economic Research.

Bruche, Max, Frederic Malherbe, and Ralf R. Meisenzahl, 2020, Pipeline risk in leveraged loan syndication, *The Review of Financial Studies* 33, 5660–5705.

Bruche, Max, Ralf R. Meisenzahl, and David X. Xu, 2026, What do lead banks learn from leveraged loan investors?, Working Paper 2023-44 Federal Reserve Bank of Chicago.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

——— , 2024, The secular decline of traditional banking: Drivers and the changing transmission of regulation and monetary policy, Working Paper 32176 National Bureau of Economic Research.

Chernenko, Sergey, Isil Erel, and Robert Prilmeier, 2022, Why do firms borrow directly from nonbanks?, *The Review of Financial Studies* 35, 4902–4947.

Chernenko, Sergey, Robert Ialenti, and David Scharfstein, 2025, Bank capital and the growth of private credit, Working paper, SSRN 5097437.

Chodorow-Reich, Gabriel, Olivier Darmouni, Stephan Luck, and Matthew Plosser, 2022, Bank liquidity provision across the firm size distribution, *Journal of Financial Economics* 144, 908–932.

Davydiuk, Tetiana, Isil Erel, Wei Jiang, and Tatyana Marchuk, 2025, Common investors

across the capital structure: Private debt funds as dual holders, Working paper.

Davydiuk, Tetiana, Tatyana Marchuk, and Samuel Rosen, 2024a, Direct lenders in the U.S. middle market, *Journal of Financial Economics* 162, 103946.

——— , 2024b, Market discipline in the direct lending space, *The Review of Financial Studies* 37, 1190–1264.

Demiroglu, Cem, and Christopher M. James, 2011, The use of bank lines of credit in corporate liquidity management: A review of empirical evidence, *Journal of Banking & Finance* 35, 775–782.

Diamond, Douglas W., 1984, Financial intermediation and delegated monitoring, *The Review of Economic Studies* 51, 393–414.

Donaldson, Jason Roderick, Naz Koont, Giorgia Piacentino, and Victoria Vanasco, 2024, A new theory of credit lines (with evidence), Working paper.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2021, Banking on deposits: Maturity transformation without interest rate risk, *Journal of Finance* 76, 1091–1143.

Elkamhi, Redouane, and Yoshio Nozawa, 2022, Fire-sale risk in the leveraged loan market, *Journal of Financial Economics* 146, 1120–1147.

Fitch Ratings, 2023, Subscription finance: A primer, Special report Fitch Ratings.

Flanagan, Thomas, and Young Soo Jang, 2026, Credit lines with(out) deposits, Working paper, SSRN 6929599.

Gatev, Evan, and Philip E. Strahan, 2006, Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market, *The Journal of Finance* 61, 867–892.

——— , 2009, Liquidity risk and syndicate structure, *Journal of Financial Economics* 93, 490–504.

Glode, Vincent, and Christian Opp, 2016, Asymmetric information and intermediation chains, *American Economic Review* 106, 2699–2721.

Greenwald, Daniel L., John Krainer, and Pascal Paul, 2025, The credit line channel, *The Journal of Finance* 80, 3137–3183.

Hanson, Samuel G., Andrei Shleifer, Jeremy C. Stein, and Robert W. Vishny, 2015, Banks as patient fixed-income investors, *Journal of Financial Economics* 117, 449–469.

Haque, Sharjil, Young Soo Jang, and Jessie Jiaxu Wang, 2025, Indirect credit supply: How bank lending to private credit shapes monetary policy transmission, Finance and Economics Discussion Series 2025-059 Board of Governors of the Federal Reserve System.

Haque, Sharjil, Simon Mayer, and Irina Stefanescu, 2024, Private debt versus bank debt in corporate borrowing, Working paper, SSRN 4821158.

Haque, Sharjil, Simon Mayer, and Teng Wang, 2026, How private equity fuels non-bank lending, *The Review of Financial Studies* Forthcoming.

Hardin, Garrett, 1968, The tragedy of the commons, *Science* 162, 1243–1248.

He, Zhiguo, Jing Huang, and Jidong Zhou, 2023, Open banking: Credit market competition when borrowers own the data, *Journal of Financial Economics* 147, 449–474.

He, Zhiguo, and Jian Li, 2026, Intermediation via credit chains, *The Journal of Finance* Forthcoming.

Holmström, Bengt, and Jean Tirole, 1998, Private and public supply of liquidity, *Journal of*

Political Economy 106, 1–40.

Huang, Jing, 2026, Fintech expansion, *The Review of Financial Studies* Forthcoming.

——— , and Erica Xuewei Jiang, 2026, Hidden aggregate risks in bank lending to NBFIs, Working paper Working paper.

Irani, Rustom M., Rajkamal Iyer, Ralf R. Meisenzahl, and José-Luis Peydró, 2021, The rise of shadow banking: Evidence from capital regulation, *The Review of Financial Studies* 34, 2181–2235.

Ivashina, Victoria, and David Scharfstein, 2010, Bank lending during the financial crisis of 2008, *Journal of Financial Economics* 97, 319–338.

Ivashina, Victoria, and Zheng Sun, 2011, Institutional demand pressure and the cost of corporate loans, *Journal of Financial Economics* 99, 500–522.

Jang, Young Soo, 2026, Are direct lenders more like banks or arm's-length investors?, *Journal of Financial Economics* Forthcoming.

——— , Dasol Kim, Amir Sufi, and Xiangyu Chen, 2025, The lending technology of direct lenders in private credit, Working Paper 34500 National Bureau of Economic Research.

Jiang, Erica Xuewei, 2023, Financing competitors: Shadow banks' funding and mortgage market competition, *The Review of Financial Studies* 36, 3861–3905.

Kashyap, Anil K., Raghuram Rajan, and Jeremy C. Stein, 2002, Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking, *The Journal of Finance* 57, 33–73.

Leland, Hayne E., 1994, Corporate debt value, bond covenants, and optimal capital struc-

ture, *The Journal of Finance* 49, 1213–1252.

Lim, Jongha, Bernadette A. Minton, and Michael S. Weisbach, 2014, Syndicated loan spreads and the composition of the syndicate, *Journal of Financial Economics* 111, 45–69.

Matvos, Gregor, Tomasz Piskorski, and Amit Seru, 2026, Private credit, balance sheets and financial stability, Working Paper 34991 National Bureau of Economic Research.

Nadauld, Taylor D., and Michael S. Weisbach, 2012, Did securitization affect the cost of corporate debt?, *Journal of Financial Economics* 105, 332–352.

Pennacchi, George, 2006, Deposit insurance, bank regulation, and financial system risks, *Journal of Monetary Economics* 53, 1–30.

Stackhouse, Chad, and Karina Velez, 2026, The liquidity lifeline: How subscription lines help BDCs and interval funds navigate redemption pressures, Fund Finance Friday, Cadwalader, Wickersham & Taft, March 27.

Sufi, Amir, 2009, Bank lines of credit in corporate finance: An empirical analysis, *The Review of Financial Studies* 22, 1057–1088.

Xu, Chi, 2025, The value of contingent liquidity from banks to nonbank lenders, Working paper University of Pennsylvania.

Xu, David X., 2026, Portfolio dynamics and the supply of safe securities, *Management Science* Articles in Advance.

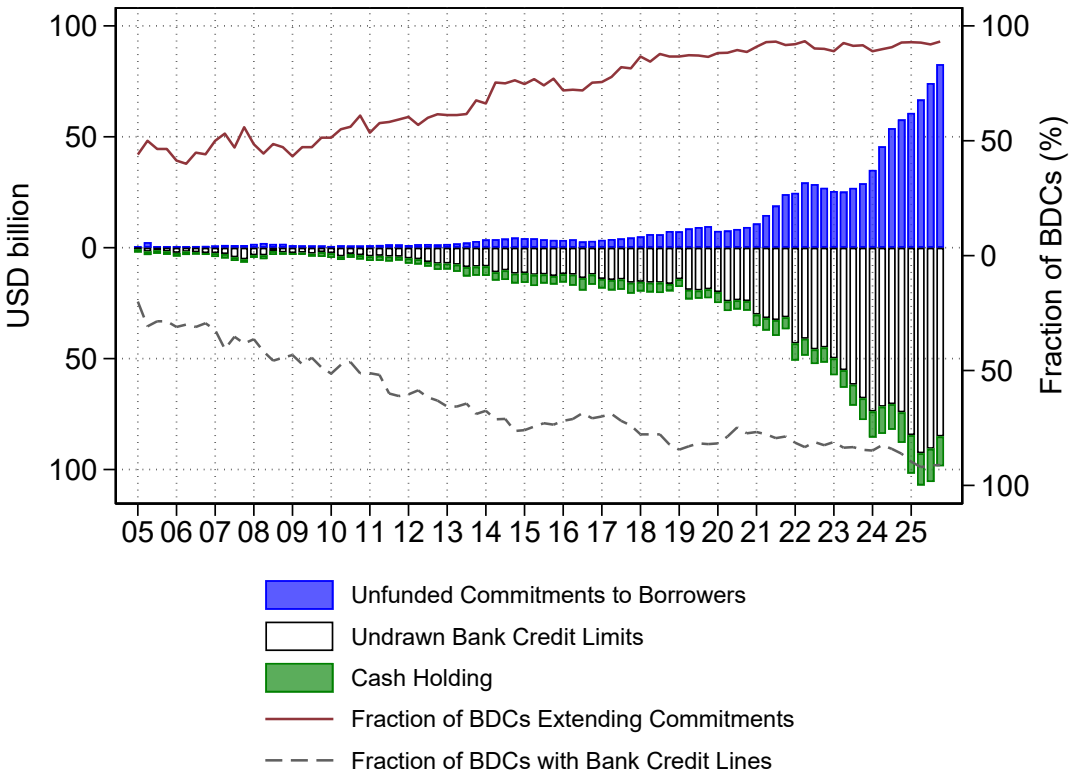


Figure 1. Liquidity Provided by and Available to BDCs.
This figure presents quarterly aggregate amounts of unfunded commitments provided by BDCs and the liquidity available to BDCs between 2005Q1 and 2025Q4. The blue bars show the dollar amount of unfunded commitments extended by BDCs to their portfolio companies. The white bars show the dollar amounts of undrawn credit limits on the bank credit lines BDCs receive as borrowers. The green bars, stacked below the white bars, show BDCs' total cash holdings. The solid red and dashed gray lines, measured against the right axis, show the fractions of the BDC universe that extend unfunded commitments to portfolio companies and that hold bank credit lines, respectively. Data sources: SEC EDGAR, Compustat, and S&P Capital IQ.

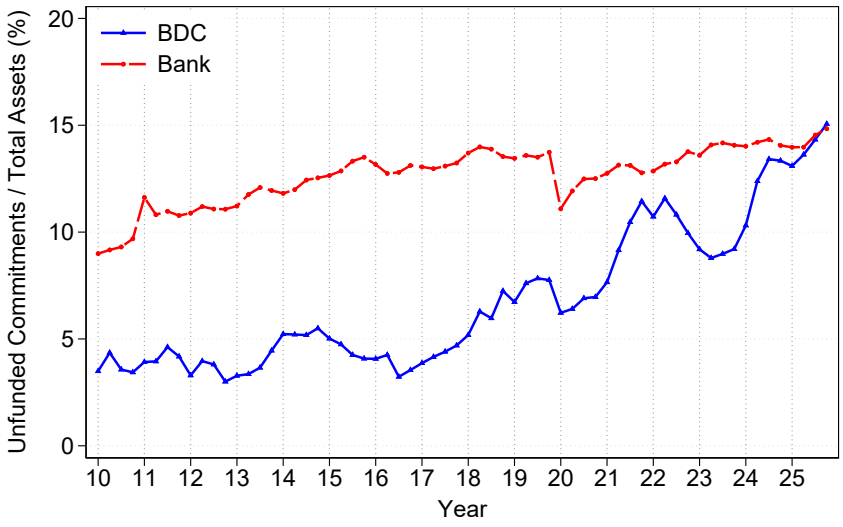
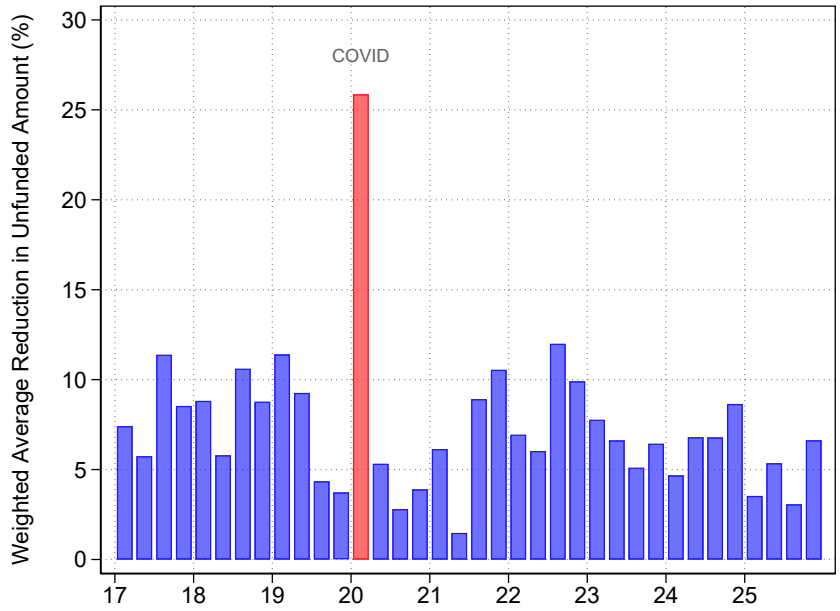


Figure 2. Liquidity Provided by Intermediaries: BDCs vs Banks.
This figure shows liquidity insurance provided by BDCs and banks to their corporate borrowers, measured as unfunded commitments divided by total assets. For BDCs, the numerator is total unfunded commitments. For banks, the numerator is the sum of "unused commitments" (Call Report Schedule RC-L) to commercial and industrial (C&I) borrowers and to financial institutions. The figure plots quarterly aggregate ratios across all banks and all BDCs from 2010Q1 to 2025Q4. Data sources: SEC's EDGAR and FFIEC's Consolidated Reports of Condition and Income.

(a) $-\%\Delta$Unfunded



(b) $\mathbf{1}(\Delta\text{Unfunded} < 0)$

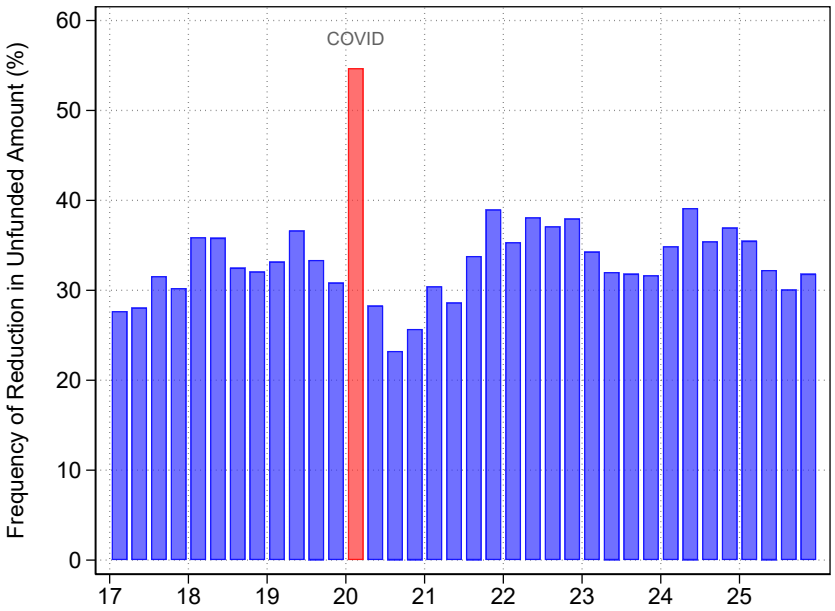


Figure 3. Changes in Unfunded Commitments.
This figure presents the time series of changes in unfunded commitments extended by BDCs to their borrowers from 2017Q1 to 2025Q4. Panel (a) shows the average quarterly reduction in unfunded commitment amounts, so that positive values indicate drawdowns. Panel (b) displays the quarterly frequency of reductions in unfunded commitment amounts. The red bar highlights 2020Q1 corresponding to the onset of the COVID-19 pandemic.

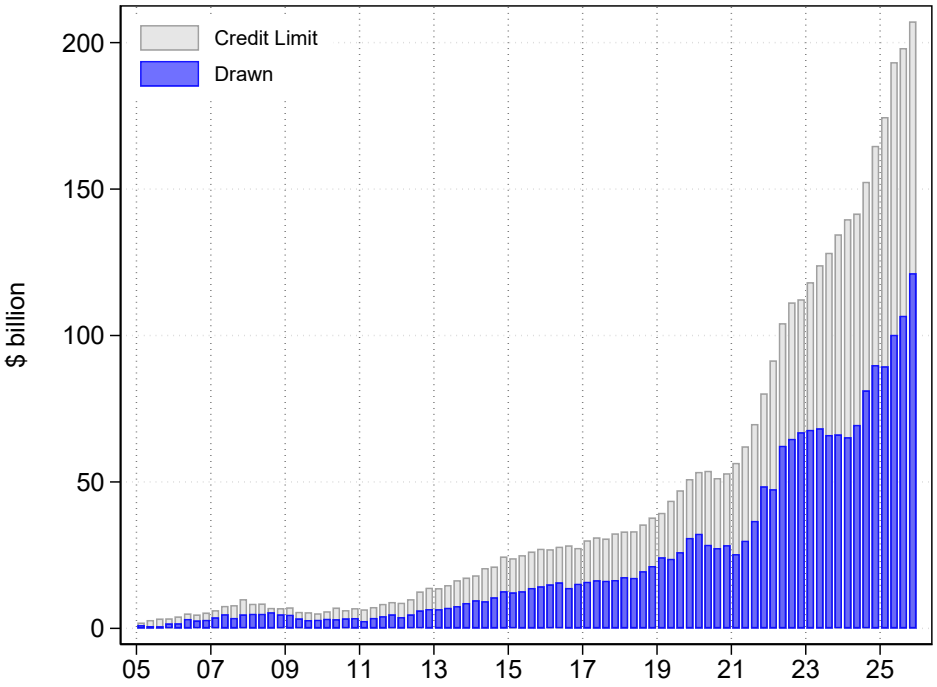


Figure 4. BDC Credit Lines from Banks: Credit Limits and Drawn Amounts. This figure plots aggregate bank credit line capacity (gray) and drawn amounts (blue) across all BDCs by quarter from 2005Q1 to 2025Q4. Credit lines are revolving facilities that BDCs obtain from banks to fund their lending and investment activities. The gap between the two bars represents the undrawn credit limit available to BDCs. Both total capacity and drawn amounts have grown steadily over the sample, reflecting the expansion of the BDC sector.

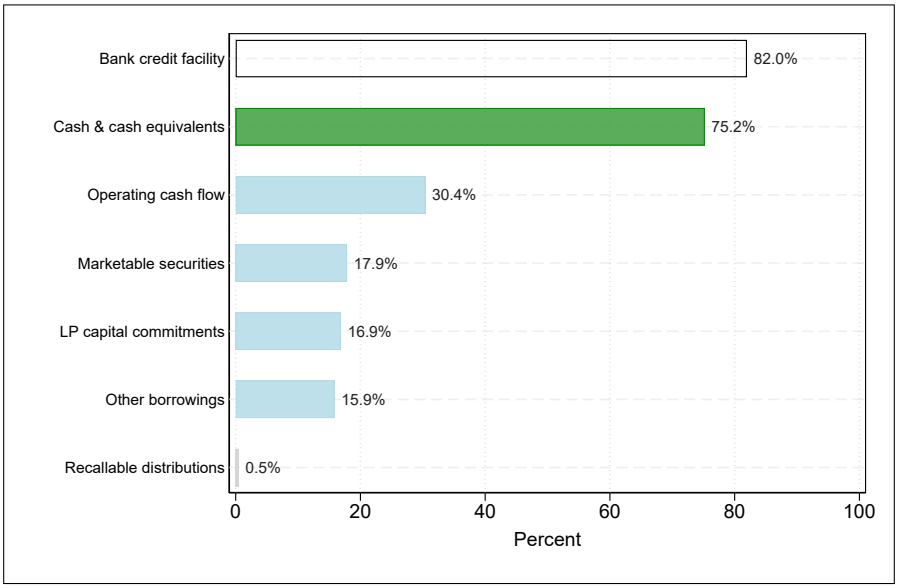


Figure 5. Liquidity Sources Disclosed as Backstop for Unfunded Commitments. This figure reports the share of BDC 10-K filings in which the BDC discusses specific sources of liquidity as backstop for its unfunded commitments to portfolio companies. The sample is restricted to the 605 10-K filings in which the BDC explicitly names at least one specific source of liquidity as backstop for unfunded commitments. Internet Appendix Figure IA.3 reports the time-series of disclosure status across the full 2006–2025 sample.

Table 1. Summary of BDC Sample

This table summarizes the BDC-quarter panel sample. Panel A reports all BDCs between 2005Q1 and 2025Q4 with non-missing balance-sheet items (total assets, total debt, equity, and cash and equivalents). *Total Assets*, *Total Debt*, *Equity*, and *Cash* are the BDC's balance-sheet items. *Total Unfunded* is the total amount of unfunded commitments the BDC extends to its borrowers. *N Bank Credit Lines* is the number of revolving credit lines the BDC obtains from its lenders, and *Bank Credit Limit* and *Undrawn Bank Credit* are the corresponding aggregate and undrawn capacity. *Dry Powder* is the BDC's uncalled investor capital commitments. Panel B reports a subsample of BDC-quarters for which details on the BDC's commitments extended to its portfolio companies are reported in regulatory filings. *N Unfunded* is the number of unfunded commitments. *Mean Unfunded* and *Median Unfunded* are the within-BDC-quarter average and median amounts of unfunded commitments to portfolio companies in $ millions. Panel C reports the fair-value share of asset classes in BDC portfolios. Senior Secured Loans includes first/second lien term loans, unitranche, and the drawn portion of senior secured revolvers and DDTLs. Joint Ventures captures equity-style interests in BDC-managed joint-venture lending vehicles whose underlying economic exposure is primarily senior secured loans. Equity includes the remaining common, preferred, warrants, and partnership/LLC interests in operating portfolio companies. Other Debt includes subordinated, mezzanine, unsecured, and convertible debt as well as structured-finance and miscellaneous positions. All amounts are measured in USD million. The sample excludes confirmed pre-operating BDC-quarters.

Panel A: All BDC-Quarters

	N	Mean	SD	P5	P25	Median	P75	P95
Total Assets	6,398	1,602.4	4,182.0	24.9	207.3	528.0	1,458.9	6,017.4
Total Debt	6,398	698.6	1,971.6	0.0	40.0	209.6	647.2	2,370.7
Equity	6,398	855.6	2,204.2	14.9	125.4	291.1	798.6	3,331.8
Cash	6,398	60.0	140.1	0.4	5.8	19.9	57.5	246.4
Total Unfunded	6,398	150.6	552.8	0.0	2.1	23.0	120.0	549.1
N Bank Credit Lines	6,398	1.5	1.6	0.0	1.0	1.0	2.0	4.0
Bank Credit Limit	6,398	594.1	1,487.7	0.0	10.0	195.0	610.0	2,035.0
Undrawn Bank Credit	6,398	271.8	706.2	0.0	0.0	75.0	250.0	1,102.0
Dry Powder	6,398	69.9	295.5	0.0	0.0	0.0	0.0	409.1

Panel B: Commitment Books

	N	Mean	SD	P5	P25	Median	P75	P95
N Unfunded	3,747	47.1	63.2	1.0	7.0	21.0	63.0	175.0
Mean Unfunded	3,747	4.1	7.0	0.4	1.1	2.4	4.8	11.9
Median Unfunded	3,747	2.9	6.4	0.2	0.8	1.6	3.2	9.2

Panel C: Portfolio Holdings

	N	Mean	SD	P5	P25	Median	P75	P95
Senior Secured Loans	5,795	73.7%	31.9%	0.0%	65.8%	87.4%	96.9%	100.0%
Joint Ventures	5,795	0.8%	3.0%	0.0%	0.0%	0.0%	0.0%	5.5%
Equity	5,795	11.8%	20.1%	0.0%	1.0%	4.8%	12.7%	59.2%
Other Debt	5,795	13.7%	23.7%	0.0%	0.0%	2.4%	14.5%	77.3%

Table 2. Summary of Unfunded Commitments Sample

This table summarizes the sample of credit commitments extended by BDCs to their individual portfolio companies between 2005Q1 and 2025Q4, at the BDC–borrower–commitment-type–quarter level. The sample requires the same borrower-commitment type to be observed in both the current and prior quarter and lagged unfunded commitment above $1 million. This filter removes originations, terminations, and small-denominator observations for which percentage changes are mechanically noisy. Panel A reports summary statistics for all commitment types. Panel B and Panel C report the corresponding statistics for revolvers and DDTLs. All amounts are measured in USD million. *Unfunded* is the unfunded amount of the credit commitment. $-\%\Delta$*Unfunded* is the negative of the percentage change in the unfunded amount from the previous period, so positive values indicate drawdowns. $\mathbf{1}(\Delta$*Unfunded* $< 0)$ is an indicator variable that equals one if the unfunded amount decreases, and zero otherwise. *Time to Maturity* is the remaining time to facility expiration in years, computed as the number of years between the expiration date and the report date (available for the subsample of commitments where the filing reports an expiration date).

	N	mean	sd	p5	p25	p50	p75	p95
Panel A: All Commitment Types								
Unfunded	82,476	6.982	13.979	1.011	1.768	3.248	7.028	24.790
$-\%\Delta$Unfunded	82,476	0.028	0.361	-0.316	0.000	0.000	0.084	0.540
$\mathbf{1}(\Delta\text{Unfunded} < 0)$	82,476	0.338	0.473	0.000	0.000	0.000	1.000	1.000
Time to Maturity	32,384	3.240	1.958	0.413	1.451	3.411	4.914	6.292
Panel B: Revolvers								
Unfunded	28,839	5.447	9.271	1.020	1.592	2.667	5.410	18.644
$-\%\Delta$Unfunded	28,839	0.003	0.304	-0.334	0.000	0.000	0.000	0.417
$\mathbf{1}(\Delta\text{Unfunded} < 0)$	28,839	0.258	0.438	0.000	0.000	0.000	1.000	1.000
Time to Maturity	12,976	4.121	1.585	1.446	3.124	4.331	5.303	6.418
Panel C: Delayed Draw Term Loans								
Unfunded	21,731	9.324	21.555	0.970	1.871	3.789	8.795	35.430
$-\%\Delta$Unfunded	21,731	0.059	0.385	-0.064	0.000	0.000	0.151	0.617
$\mathbf{1}(\Delta\text{Unfunded} < 0)$	21,731	0.411	0.492	0.000	0.000	0.000	1.000	1.000
Time to Maturity	11,849	2.164	1.836	0.277	0.914	1.462	3.195	6.048

Table 3. Magnitude of BDC-Level Liquidity Shocks from Commitment Books

This table reports the estimated magnitude of BDC-level liquidity shocks from the commitment book. The sample consists of 2,792 BDC-quarters of 79 BDCs with at least 12 quarters between 2005Q1 and 2025Q4 in which the BDC has at least 5 continuing borrowers in its commitment book. For each BDC ℓ, σ_ℓ is the time-series standard deviation of its quarterly liquidity shock from the commitment book, estimated as the dollar-weighted average of $-\%\Delta Unfunded_{i,\ell,t}$ across continuing borrowers. The dollar-valued liquidity shock associated with a one-standard-deviation quarterly BDC-level liquidity shock is estimated as $\widehat{\sigma}^{\$}_{\ell t} \equiv \sigma_\ell \times$Total Unfunded$_{\ell,t-1}$, where Total Unfunded$_{\ell,t-1}$ is the BDC's lagged total unfunded commitments. Column 3 reports the median ratio of this dollar-valued liquidity shock to lagged cash holdings across BDC-quarters. Column 4 reports the fraction of BDC-quarters with dollar-valued liquidity shock exceeding lagged cash holdings. Rows 2–4 split the sample into terciles by the ratio of Total Unfunded to Total Assets.

	N	Median Total Unfunded/TA	Median Shock/Cash	Fraction with Shock>Cash
	(1)	(2)	(3)	(4)
All BDC-quarters	2,792	0.069	0.245	0.153
Total Unfunded / TA: Low	931	0.023	0.066	0.029
Total Unfunded / TA: Mid	931	0.069	0.298	0.141
Total Unfunded / TA: High	930	0.140	0.557	0.289

Table 4. Concentration of BDCs' Commitment Books

This table compares the concentration of BDCs' unfunded commitments to the concentration of their debt-only portfolio holdings. The sample consists of 3,235 BDC-quarters with data on both the commitment book and portfolio holdings and identified sponsor exposure in both books. Industry, HQ-state, and sponsor measures are computed on this common set of BDC-quarters. For each BDC-quarter, concentration is summarized at three levels of aggregation (borrower industry group, HQ state, and sponsor) using two measures: the Herfindahl–Hirschman index $\sum_i w_i^2$, where w_i is the entity's share of total unfunded commitment (or fair-value of debt holdings); and the Top-3 share, the sum of the three largest weights. Each row reports the cross-sectional mean and quartiles across BDC-quarters, separately under commitment book weights (columns 1–4) and loan portfolio weights (columns 5–8). The Diff column reports the mean within-BDC-quarter difference between the unfunded and holdings values, with significance from a paired t-test, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: HHI

	Commitment Book				Loan Portfolio				Diff
	Mean	P25	Median	P75	Mean	P25	Median	P75	Paired t
Industry	0.296	0.163	0.225	0.356	0.162	0.104	0.132	0.185	0.134***
HQ State	0.249	0.096	0.177	0.307	0.102	0.063	0.077	0.109	0.148***
Sponsor	0.279	0.073	0.164	0.371	0.069	0.030	0.044	0.073	0.210***
N					3,235				

Panel B: Top-3 Share

	Commitment Book				Loan Portfolio				Diff
	Mean	P25	Median	P75	Mean	P25	Median	P75	Paired t
Industry	0.737	0.600	0.720	0.872	0.562	0.464	0.537	0.641	0.175***
HQ State	0.636	0.425	0.619	0.827	0.414	0.320	0.374	0.466	0.222***
Sponsor	0.619	0.351	0.592	0.931	0.290	0.183	0.239	0.345	0.329***
N					3,235				

Table 5. Variance Decomposition of Liquidity Shocks from Commitment Books

This table reports R^2s from regressing borrower-level liquidity shocks on each of four fixed-effect specifications: year-quarter, industry-year-quarter, HQ state-year-quarter, and BDC-year-quarter. The sample consists of BDC-borrower-quarters in continuing unfunded facilities (excluding originations and terminations) with $Unfunded_{i,\ell,t-1} > \$1$ million between 2005Q1 and 2025Q4. Industry is the borrower's industry classification; HQ state is the borrower's headquarters state (HQ country used for foreign borrowers). The outcome is either the continuous shock $-\%\Delta Unfunded_{i,\ell,t}$ or the binary shock $\mathbf{1}\{\Delta Unfunded_{i,\ell,t} < 0\}$; OLS columns weight all observations equally, WLS columns use $Unfunded_{i,\ell,t-1}$ as weights.

	$-\%\Delta$Unfunded		$\mathbf{1}(\Delta\text{Unfunded} < 0)$	
	OLS	WLS	OLS	WLS
	(1)	(2)	(3)	(4)
Year-Quarter FEs	0.007	0.010	0.010	0.011
Industry-Year-Quarter FEs	0.036	0.061	0.063	0.097
HQ State-Year-Quarter FEs	0.053	0.091	0.076	0.117
BDC-Year-Quarter FEs	0.065	0.069	0.078	0.088
N	76,685	76,685	76,685	76,685

Table 6. Commonality in Liquidity Shocks from Commitment Books

This table reports regressions of borrower-level liquidity shocks from commitment books on public firm credit line drawdowns or market-wide factors. The sample consists of BDC-borrower-quarters with at least $1 million in continuing unfunded facilities (excluding originations and terminations) between 2010Q1 and 2024Q4. The dependent variable is either the continuous shock $-\%\Delta Unfunded_{i,\ell,t}$ or the binary shock $\mathbf{1}\{\Delta Unfunded_{i,\ell,t} < 0\}$. In Panel A, the regressors are quarterly average credit line drawdown among S&P Capital IQ public firms, stratified by lagged Debt/EBITDA buckets. In Panel B, the regressors are macro and credit factors. Standard errors are clustered by quarter, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Public Firm Average Drawdown

Debt/EBITDA:	$[0,2)$	$[2,4)$	≥ 4	< 0
	(1)	(2)	(3)	(4)
		$-\%\Delta\,Unfunded$		
$\hat{\beta}$	0.023	0.057	0.151**	0.068***
t	(1.021)	(1.631)	(2.208)	(6.328)
R^2	0.000	0.002	0.003	0.002
		$\mathbf{1}(\Delta\,Unfunded < 0)$		
$\hat{\beta}$	−0.006	0.088***	0.282***	0.073***
t	(−0.163)	(3.030)	(3.847)	(3.302)
R^2	0.000	0.004	0.006	0.001
N	53,484	53,484	53,484	53,484

Panel B: Market-Wide Factors

Factors:	ΔBBB	ΔHY	SP500	ΔVIX
	(1)	(2)	(3)	(4)
		$-\%\Delta\,Unfunded$		
$\hat{\beta}$	0.049***	0.019*	−0.226*	0.002
t	(2.656)	(1.852)	(−1.789)	(1.438)
R^2	0.003	0.002	0.002	0.002
		$\mathbf{1}(\Delta\,Unfunded < 0)$		
$\hat{\beta}$	0.067***	0.029***	−0.278**	0.003***
t	(5.223)	(3.278)	(−2.227)	(2.613)
R^2	0.004	0.003	0.002	0.003
N	53,484	53,484	53,484	53,484

Table 7. BDC Commitments as Partial Liquidity Insurance

This table estimates BDCs' liquidity backstop for their unfunded commitments. Panel A reports results of regressing liquidity available to a BDC on its total unfunded commitments extended to borrower firms. Every observation in the sample is a BDC-quarter with a bank credit line in 2005Q1–2025Q4. The dependent variable is the BDC's total undrawn bank credit across its facilities in column 1, and the sum of the BDC's undrawn bank credit and cash holdings in column 2, both scaled by lagged total assets. *Total Unfunded/TA* is the BDC's total unfunded commitments extended to borrowers on its commitment book, scaled by lagged total assets. *Debt/TA* is the BDC's lagged total debt scaled by lagged total assets. log(*TA*) is the natural logarithm of the BDC's lagged total assets. *Listed* is an indicator that equals one if the BDC is exchange-listed in the quarter. Standard errors are clustered at the BDC level. *, **, and *** represent 10%, 5%, and 1% levels of statistical significance. The p-value row tests $H_0 : \beta \geq 1$ against $H_1 : \beta < 1$ for the coefficient on *Total Unfunded/TA*. Panel B reports the fraction of BDC-quarters in which the indicated multiple of the dollar-valued liquidity shock $\widehat{\sigma}^{\$}_{\ell t}$ in Table 3 would exceed the estimated liquidity backstop $\widehat{\beta} \times \text{Total Unfunded}_{\ell,t-1}$, using the coefficient from Panel A.

Panel A: Liquidity Backstop for Unfunded Commitments

	Undrawn Bank Credit	Undrawn Bank Credit + Cash
	(1)	(2)
Total Unfunded / TA	0.448***	0.607***
	(0.110)	(0.132)
Debt / TA	−0.136	−0.145
	(0.090)	(0.120)
log(TA)	−0.158***	−0.216***
	(0.016)	(0.021)
Listed	0.069	0.065
	(0.042)	(0.048)
BDC FEs	Y	Y
Year-Quarter FEs	Y	Y
R^2	0.565	0.571
N	4,699	4,699
p-value ($H_0 : \beta \geq 1$)	0.000	0.002

Panel B: BDC-Level Liquidity Shock > Liquidity Backstop

	Undrawn Bank Credit	Undrawn Bank Credit + Cash
	(1)	(2)
$1 \times \widehat{\sigma}^{\$}_{\ell t}$	0.000	0.000
$2 \times \widehat{\sigma}^{\$}_{\ell t}$	0.063	0.036
$3 \times \widehat{\sigma}^{\$}_{\ell t}$	0.182	0.090

Table 8. BDC Liquidity Conditions and Rationing of Borrower Drawdowns

This table reports the estimated relationship between BDC liquidity conditions and borrower drawdowns. The sample is a BDC–borrower–quarter panel of unfunded commitments between 2010Q1 and 2024Q4. In columns 1–4, the dependent variable is the borrower's net drawdown, proxied by the decrease in its unfunded commitment, $-\%\Delta Unfunded$, i.e., positive values indicate draws. In columns 5 and 6, the dependent variables are the decrease and increase parts of the net drawdown, respectively. Industry Peer Drawdown is the positive part of the standardized average credit line drawdown rate among high-leverage public firms (lagged Debt/EBITDA of at least four) in the borrower's Fama–French 12 industry that quarter. Liquidity Tightness is the ratio of the BDC's total unfunded commitments to its cash plus undrawn bank credit, lagged one quarter. Column 1 interacts Industry Peer Drawdown with standardized log Liquidity Tightness. Columns 2–4 replace the continuous Liquidity Tightness with indicators that Tightness exceeds 100%, 120%, and 150%. Columns 5 and 6 repeat column 1 for the decrease and increase parts of the outcome. All columns are estimated by weighted least squares with weights equal to lagged unfunded commitment, and cluster standard errors at the BDC level; *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Borrower Drawdown

	Net Drawdown				Decreases	Increases
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Peer Drawdown						
× BDC Liquidity Tightness	−0.016**				−0.012***	0.005
	(0.006)				(0.004)	(0.004)
× **1**{Tightness > 100%}		−0.027*				
		(0.015)				
× **1**{Tightness > 120%}			−0.040**			
			(0.016)			
× **1**{Tightness > 150%}				−0.058***		
				(0.019)		
BDC-Borrower FEs	Y	Y	Y	Y	Y	Y
BDC-Year-Quarter FEs	Y	Y	Y	Y	Y	Y
Industry-Year-Quarter FEs	Y	Y	Y	Y	Y	Y
N	39,067	39,067	39,067	39,067	39,067	39,067

Appendix A Proofs

A.1 Direct Bank Lending

The benchmark holds the existing book and funding technology fixed but removes the BDC-level resolution cost. For every shocked firm, increasing continuation by one unit raises surplus by $y - R\rho_i > 0$. Thus all shocked firms continue. Taking expectations gives the full-insurance surplus $n\Big[y - R\Big(1 + p\,\mathbb{E}[\rho_i \mid \rho_i > 0]\Big)\Big] - np\lambda$; the expected firm bankruptcy cost $np\lambda$ is common to all insurance policies.

The premium implementation below gives the lender expected private profit

$$n\left[y - R\left(1 + p\,\mathbb{E}[\rho_i \mid \rho_i > 0]\right)\right] - \Delta n(1-p) \tag{16}$$

before any fixed regulatory charge. If initial entry is optional, this expression must cover that charge. Otherwise the lender does not finance the book. Conditional on entry, a fixed charge does not change the optimal continuation policy. This is distinct from a marginal charge on each additional dollar advanced, which changes the continuation return itself. Our insurance analysis is conditional on the existing book; it does not impose entry under parameters that violate participation.

A.2 Proof of Proposition 1

This part first establishes lemmas that pin down the contract terms other than the limits: the continuation rule (smallest first), the rate ($R_N = y - \Delta$), and the fees (ϕ_N and ϕ_B), and then proves the proposition, for a book of $n \geq 2$ firms.

With n firms, the BDC's problem (10) becomes

$$\begin{aligned}
\max_{\substack{\mathcal{C}:\,\underline{\rho}\leq\ell\leq\bar{\rho},\\ 0\leq L\leq n\ell}} \quad & V(\mathcal{C}) \;\equiv\; R\,(n\phi_N - \phi_B) + \mathbb{E}\Big[\max\{\Pi, 0\}\Big] - n\lambda\,\Pr(\Pi < 0) \\
\text{s.t.} \quad & R\,\phi_B \geq \mathbb{E}\Big[\max\{-\Pi, 0\}\Big] && \text{(Bank PC)} \\
& R\,\phi_N \leq (1-p)(y - \Delta - R_N) + p\,\Delta\,\mathbb{E}\Big[x_i \mid \rho_i > 0\Big] && \text{(Firm PC)} \\
& \rho_i x_i \leq \ell, \quad 0 \leq x_i \leq 1, \quad \sum_{\rho_i > 0} \rho_i x_i \leq L && \text{(Credit Limits)}
\end{aligned} \tag{17}$$

The firm credit limit is a dollar limit: a shocked firm can draw up to $\min\{\rho_i, \ell\}$, including partial funding when $\rho_i > \ell$. The commitment to honor these draws up to the bank credit limit requires $\sum_{\rho_i>0} \rho_i x_i = \min\{L, \sum_{\rho_i>0} \min\{\rho_i, \ell\}\}$.

We spell out the BDC's net worth at $t = 2$ with n firms:

$$\begin{aligned}\Pi(\boldsymbol{\rho}; \mathcal{C}) &= R_N \sum_{i=1}^{n} \mathbf{1}\{\rho_i = 0\} + \sum_{\rho_i>0} \min\Big\{R_N(1+\rho_i x_i),\, (y-\Delta)x_i\Big\} - R\Big(n + \sum_{\rho_i>0} \rho_i x_i\Big) \\ &= R_N \sum_{i=1}^{n} \mathbf{1}\{\rho_i = 0\} + (y-\Delta) \sum_{\rho_i>0} x_i - R\Big(n + \sum_{\rho_i>0} \rho_i x_i\Big).\end{aligned} \tag{18}$$

The fees settle at $t = 0$ and do not enter. An unshocked firm owes the face value R_N on its term loan and repays it in full. A shocked firm continued at fraction x_i owes $R_N(1 + \rho_i x_i)$, the term loan plus its draw, and repays the smaller of this face value and its pledgeable income $(y - \Delta)x_i$. The BDC's repayment to the bank is $R\Big(n + \sum_{\rho_i>0} \rho_i x_i\Big)$, the bank term loan plus its draws. The second equality holds because Assumption 1 and $R_N \geq R$ imply that every shocked firm defaults regardless of the contract, and therefore pays $(y - \Delta)x_i$:

$$R_N(1 + \rho_i x_i) - (y - \Delta)x_i \;\geq\; R + \Big[R\rho_i - (y - \Delta)\Big]x_i \;>\; 0. \tag{19}$$

Rates below R leave collections short of the repayment to the bank in every state and are never optimal.

A.2.1 Lemmas

Lemma A.1 (No self-insurance)**.** *Suppose the firm's cash satisfies $c < \frac{R\underline{\rho}}{y-\Delta}$ and the rent satisfies $\Delta < R\underline{\rho}$. A shocked firm does not save its own cash to inject liquidity upon shocks.*

Proof. Let the shareholders of a shocked firm continued at fraction x_i inject $s \leq c$, raising continuation to $x_i + \frac{s}{\rho_i}$. By (19), its obligation net of pledgeable income satisfies[21]

$$R_N(1 + \rho_i x_i) - (y - \Delta)\Big(x_i + \frac{s}{\rho_i}\Big) \;\geq\; R - \frac{(y - \Delta)\, c}{\underline{\rho}} \;>\; 0,$$

where the first inequality uses $y - \Delta < R\underline{\rho} \leq R\rho_i$ (Assumption 1) and $R_N \geq R$, as in (19),

[21] This condition assumes away new senior debt that dilutes the existing term loan, which would make continuation easier by lowering the cash shareholders must inject below ρ_i. Assumption 1 alone rules out only a pure senior loan without an own-cash injection.

together with $s \le c$ and $\rho_i \ge \underline{\rho}$; the case $x_i = 0$ covers an uninsured firm. The firm thus defaults at every feasible injection. An injected dollar returns only the rent $\frac{\Delta}{\rho_i} \le \frac{\Delta}{\underline{\rho}} < R$: investing the cash outside strictly dominates, and no cash is injected. □

Lemma A.2 (Continuation rule)**.** *Given the contract $\mathcal{C}$, the optimal continuation follows the smallest-shock-first rule*

$$x_{(j)} = \min\left\{1, \frac{\ell}{\rho_{(j)}}, \frac{\max\left\{L - \sum_{r<j} \min\{\rho_{(r)}, \ell\}, 0\right\}}{\rho_{(j)}}\right\}, \tag{20}$$

where $\rho_{(1)} \le \cdots \le \rho_{(k)}$ orders the positive shocks. At most one firm receives a positive draw below $\min\{\rho_i, \ell\}$, and ties have probability zero. Several firms may be partially continued because their individual credit limits bind.

Proof. Suppose a rule $\{x_i\}$ fails smallest-first priority on a positive-probability event: there are firms i and j with $0 < \rho_i < \rho_j$, $x_j > 0$, and $\rho_i x_i < \min\{\rho_i, \ell\}$. On this event, define the rule $\{x_i'\}$ by

$$x_i' = x_i + \frac{\varepsilon}{\rho_i}, \qquad x_j' = x_j - \frac{\varepsilon}{\rho_j}, \qquad \varepsilon = \min\left\{\rho_j x_j,\ \min\{\rho_i, \ell\} - \rho_i x_i\right\} > 0, \tag{21}$$

and $x_i' = x_i$ for all i elsewhere. The exchange reallocates ε dollars of committed funding between the two draws: total draws, and hence the repayment to the bank, are unchanged in every state, while total continuation rises by $\varepsilon(\frac{1}{\rho_i} - \frac{1}{\rho_j}) > 0$. By (18), net worth rises by $(y - \Delta)\,\varepsilon(\frac{1}{\rho_i} - \frac{1}{\rho_j}) \ge 0$ state by state, so in the objective of (17), $\mathbb{E}[\max\{\Pi, 0\}]$ weakly rises and $\Pr(\Pi < 0)$ weakly falls: the payoff weakly improves at any fees. Completing these exchanges gives a symmetric rule that maximizes total continuation in every state. Its common expected continuation conditional on a shock is at least the average, and hence the lowest, under the original rule. Thus the original common firm fee remains feasible; the bank's constraint also weakly relaxes. Therefore, the rule in (20) is optimal. Under this rule, at most one firm receives a positive draw below its permitted request. □

Lemma A.3 (Fees and optimal rate)**.** *The bank fee prices the expected credit loss, $R\phi_B = \mathbb{E}[\max\{-\Pi, 0\}]$. The optimal rate is $R_N = y - \Delta$, and the fee charged to each firm is $R\phi_N = p\Delta\,\mathbb{E}[x_i \mid \rho_i > 0]$.*

Proof. The bank's participation constraint in (17) binds at any optimum: the bank fee enters the BDC's payoff one for one, so the BDC never pays more than the bank's expected credit

loss. The firm's participation constraint in (17) rearranges to

$$R\phi_N \le \underbrace{(1-p)(y-R_N) + p\,\Delta\,\mathbb{E}\left[x_i \mid \rho_i > 0\right]}_{\text{with credit line}} - \underbrace{(1-p)\Delta}_{\text{term loan only}}, \qquad \phi_N \le c: \tag{22}$$

the firm keeps $y - R_N$ when unshocked and the rent Δx_i when shocked, since by (19) it defaults and pays $(y-\Delta)x_i$; its outside option, the term loan alone, pays $(1-p)\Delta$. There is no bankruptcy cost because The firm faces the same bankruptcy cost—which occurs whenever shocked—regardless of insurance. Under the smallest-first rule of Lemma A.2, the conditional coverage $\mathbb{E}[x_i \mid \rho_i > 0]$ is common to all firms.

Substituting the binding bank constraint and the participation bound (22) into the objective of (17), the BDC's payoff satisfies

$$V(\mathcal{C}) \;\le\; \mathbb{E}\Big[y\Big(\sum_{i=1}^{n}\mathbf{1}\{\rho_i=0\} + \sum_{\rho_i>0} x_i\Big) - R\Big(n + \sum_{\rho_i>0}\rho_i x_i\Big)\Big] - n(1-p)\Delta - n\lambda\,\Pr(\Pi<0). \tag{23}$$

The bound depends on the rate only through the bankruptcy probability: a higher rate raises unshocked firms' repayments and leaves shocked firms' unchanged, so $\Pr(\Pi<0)$ weakly falls and the bound is largest at $R_N = y - \Delta$. At this rate the premium $R\phi_N = p\Delta\,\mathbb{E}[x_i \mid \rho_i > 0] \le p\Delta \le Rc$ is affordable, the firm's constraint binds, and the bound is attained: $R_N = y - \Delta$ is optimal. □

Lemma A.4 (Constrained efficiency)**.** *The BDC's problem* (17) *solves for the constrained-efficient allocation within the class of term loans and credit lines.*

Proof. With both fees binding (Lemma A.3), (23) holds with equality:

$$V(\mathcal{C}) = W(\mathcal{C}) - nRc + np\lambda - n(1-p)\Delta, \tag{24}$$

where $W(\mathcal{C})$ is the expected total surplus of the chain, including shareholder value. The three adjustment terms in (24) are constant to the contract. First, the $t = 0$ fees only redistribute the cash:

$$\underbrace{nR(c-\phi_N)}_{\text{firm shareholders}} + \underbrace{R(n\phi_N - \phi_B)}_{\text{BDC shareholders}} + \underbrace{R\phi_B}_{\text{bank}} = nRc,$$

so the cash contributes the constant nRc to $W(\mathcal{C})$ under every contract. Second, a shocked

firm's obligation exceeds its pledgeable income at every continuation fraction $x_i \in [0,1]$, including $x_i = 0$: as in (19),

$$R_N(1+\rho_i x_i) - (y-\Delta)x_i \;\geq\; R + \Big[R\rho_i - (y-\Delta)\Big]x_i \;\geq\; R \;>\; 0,$$

where the first inequality uses $R_N \geq R$ and the second uses $y - \Delta < R\rho_i$ (Assumption 1). Each shocked firm thus incurs the loss λ under every contract, while unshocked firms repay, so the firms' expected bankruptcy losses are the constant $np\lambda$. Third, the firms' fixed outside payoff $n(1-p)\Delta$ accrues to them regardless of coverage. Hence, at the rule and rate of Lemmas A.2 and A.3, maximizing the BDC's payoff is maximizing surplus:

$$(\ell^*, L^*) \in \arg\max_{\underline{\rho}\leq\ell\leq\bar{\rho},\, 0\leq L\leq n\ell} W^N(\ell, L), \tag{25}$$

where

$$W^N(\ell,L) = \mathbb{E}\Big[y\Big(\sum_{i=1}^{n}\mathbf{1}\{\rho_i = 0\} + \sum_{\rho_i>0} x_i\Big) - R\Big(n + \sum_{\rho_i>0}\rho_i x_i\Big)\Big] - np\lambda - n\lambda\Pr(\Pi<0) + nRc, \tag{26}$$

with $\{x_i\}$ the smallest-first rule (20). □

A.2.2 Proof of Proposition 1

Proof. By Lemmas A.2–A.4, we only need to pin down the credit line limits in the contract, ℓ and L, and the problem reduces to

$$\max_{\underline{\rho}\leq\ell\leq\bar{\rho},\, 0\leq L\leq n\ell} V(\ell,L) \equiv \underbrace{\mathbb{E}\Big[\sum_{\rho_i>0}(y-R\rho_i)\,x_i\Big]}_{\text{continuation surplus}} - \underbrace{n\lambda\,\Pr\Big(\Pi(\boldsymbol{\rho};\ell,L)<0\Big)}_{\text{expected bankruptcy cost}}, \tag{27}$$

where $\{x_i\}$ satisfy the smallest-first rule (20) at the limits (ℓ, L) and, with abuse of notation, we write the BDC's net worth $\Pi(\boldsymbol{\rho};\ell,L)$ and payoff $V(\ell,L)$. Hence, a contract dominates another when it gains more continuation surplus than it adds in expected bankruptcy cost. Throughout the proof, $k = \sum_{i=1}^{n}\mathbf{1}\{\rho_i > 0\}$ denotes the number of shocked firms.

The proof proceeds as follows. After a brief discussion on primitive assumption, we prove part (i) and the existence of an optimum. Part (ii) then takes three steps: Step 1 excludes small bank credit lines, for any firm credit line size; Step 2 establishes full firm credit lines

($\ell = \bar{\rho}$); Step 3 excludes a full bank credit line ($L = n\bar{\rho}$).

Primitive conditions. Part (ii) requires the loan book to absorb an isolated draw,

$$n(y - \Delta) > R(n + \bar{\rho}), \tag{28}$$

and the following two joint restrictions on (p, λ). As in the setup, positive shocks are independent and uniform on $[\underline{\rho}, \bar{\rho}]$; $R_N = y - \Delta$. The corner is understood up to allocation-equivalent firm credit limits. First, concurrent shocks must be sufficiently rare relative to the bankruptcy cost:

$$\left(\frac{y}{\bar{\rho}} - R\right)(1-p)^{n-1} > n\lambda \frac{R\bar{\rho}^2}{R_N \underline{\rho}(\bar{\rho} - \underline{\rho})}[1 - (1-p)^{n-1}]. \tag{29}$$

Equivalently, $p < \hat{p}$, where

$$\hat{p} = 1 - \left[\frac{n\lambda R\bar{\rho}^2}{n\lambda R\bar{\rho}^2 + \left(\frac{y}{\bar{\rho}} - R\right) R_N \underline{\rho}(\bar{\rho} - \underline{\rho})}\right]^{1/(n-1)}. \tag{30}$$

Second, the bankruptcy cost must be sufficiently large: $\lambda > \hat{\lambda}$, where

$$\hat{\lambda} \equiv \frac{\mathbb{E}\Big[\sum_{\rho_i > 0}(y - R\rho_i)\{1 - x_i(\bar{\rho}, \bar{\rho})\}\Big]}{n\Big[\Pr(\Pi(\boldsymbol{\rho}; \bar{\rho}, n\bar{\rho}) < 0) - \Pr(\Pi(\boldsymbol{\rho}; \bar{\rho}, \bar{\rho}) < 0)\Big]}. \tag{31}$$

The denominator is required to be strictly positive; otherwise this comparison does not establish partial insurance. The first condition, a small shock probability, is sufficient for the insurance benefits of increasing the firm credit lines to dominate the risk of loading the BDC with a large face value and pushing it into bankruptcy, as concurrent large shocks are unlikely. The second condition says that the bankruptcy cost is sufficiently high for the choice of L to be relevant in containing it.

Part (i): first best when $\lambda = 0$. When $\lambda = 0$, only the continuation surplus in (27) remains, and each unit continued yields $y - R\rho_i > 0$. The contract $(\bar{\rho}, n\bar{\rho})$ attains $x_i = 1$ for every shock, whereas any $\ell < \bar{\rho}$ or $L < n\bar{\rho}$ reduces continuation with positive probability, by full support and independence. This proves part (i). An optimum exists for every $\lambda \geq 0$:

the feasible set of limits is compact, the continuation rule and net worth are continuous in the limits, and $\mathbf{1}\{\Pi < 0\}$ is lower semicontinuous. Hence the expected payoff is upper semicontinuous and attains its maximum.

Part (ii), Step 1: a uniform lower bound on the bank credit line. Take any feasible (ℓ, L) with

$$L \leq \frac{2\underline{\rho}\bar{\rho}}{\underline{\rho} + 2\bar{\rho}}. \tag{32}$$

Compare it with $(\bar{\rho}, \bar{\rho})$. The latter increases both credit limits, so every firm's continuation weakly increases in this comparison: the original $L < \underline{\rho} \leq \ell$ makes individual limits nonbinding, as does $\ell = \bar{\rho}$ in the comparison contract. Its productive surplus gain is nonnegative in every state.

When exactly one firm is shocked, the original contract continues at most

$$\frac{L}{\underline{\rho}} \leq \frac{2\bar{\rho}}{\underline{\rho} + 2\bar{\rho}} \tag{33}$$

of that firm. This bound also applies when $\rho_i > \ell$, since its draw cannot exceed L. The comparison contract continues the firm fully. Its productive gain is at least

$$(y - R\bar{\rho})\frac{\underline{\rho}}{\underline{\rho} + 2\bar{\rho}}. \tag{34}$$

In zero- and one-shock states, $(\bar{\rho}, \bar{\rho})$ continues all projects with draws at most $\bar{\rho}$. Condition (28) therefore implies

$$\Pi(\boldsymbol{\rho}; \bar{\rho}, \bar{\rho}) > 0 \qquad \text{when } k = 0, 1. \tag{35}$$

The switch to $(\bar{\rho}, \bar{\rho})$ raises the default probability by at most

$$\Pr(\Pi(\boldsymbol{\rho}; \bar{\rho}, \bar{\rho}) < 0) - \Pr(\Pi(\boldsymbol{\rho}; \ell, L) < 0) \;\leq\; \Pr\Big(\Pi(\boldsymbol{\rho}; \bar{\rho}, \bar{\rho}) < 0,\; \Pi(\boldsymbol{\rho}; \ell, L) \geq 0\Big) \;\leq\; \Pr(k \geq 2). \tag{36}$$

The first inequality drops the states in which only the original contract (ℓ, L) defaults. The second inequality uses (35): the comparison contract defaults only when $k \geq 2$.

Combining the productive gain and the bound on BDC losses gives

$$V(\bar{\rho},\bar{\rho}) - V(\ell, L) \geq np(1-p)^{n-1}(y - R\bar{\rho})\frac{\underline{\rho}}{\underline{\rho} + 2\bar{\rho}} - n\lambda \Pr(k \geq 2). \tag{37}$$

For the binomial distribution,

$$2\Pr(k \geq 2) \leq \mathbb{E}[k\mathbf{1}\{k \geq 2\}] = np[1 - (1-p)^{n-1}]. \tag{38}$$

Substitution yields

$$V(\bar{\rho},\bar{\rho}) - V(\ell, L) \geq \frac{np}{2}\left[\frac{2\underline{\rho}}{\underline{\rho} + 2\bar{\rho}}(y - R\bar{\rho})(1-p)^{n-1} - n\lambda[1 - (1-p)^{n-1}]\right] > 0, \tag{39}$$

where the strict inequality follows from (29), which is stronger than the required bound because $\frac{R_N\underline{\rho}(\bar{\rho}-\underline{\rho})}{R\bar{\rho}^3} < \frac{2\underline{\rho}}{\underline{\rho}+2\bar{\rho}}$ under $R_N < R\underline{\rho}$. Thus every optimal contract has L strictly above the bound in (32).

Part (ii), Step 2: full firm credit lines ($\ell^* = \bar{\rho}$). Fix any firm credit limit $\ell < \bar{\rho}$ and feasible bank credit limit above the bound in Step 1, $L > \frac{2\underline{\rho}\bar{\rho}}{\underline{\rho}+2\bar{\rho}}$. Compare the original contract (ℓ, L) with the expanded contract $(\bar{\rho}, L)$, at the same bank credit limit. If $\ell \geq L$, the allocations coincide; consider $\ell < L$. A shock in $(\ell, \bar{\rho}]$ can receive a larger draw under the expanded contract; funding is reallocated as necessary under the smallest-first rule (20). The change weakly increases productive surplus, but may also add bankruptcy costs to the BDC. Below, we bound the two parts and show that the expansion dominates under the small-shock-probability condition (29).

Consider first the states in which exactly one firm is shocked and its shock lies in $(\ell, \bar{\rho}]$, which occurs with probability

$$np\,\Pr(\rho_i > \ell \mid \rho_i > 0)(1-p)^{n-1}. \tag{40}$$

The shocked firm is continued at fraction $\frac{\ell}{\rho_i}$ under the original contract, while the new contract that increases firm credit limit continues the shocked project at the fraction $x_i =$

$\min\left\{1, \frac{L}{\rho_i}\right\}$, giving the continuation gain

$$\min\left\{1, \frac{L}{\rho_i}\right\} - \frac{\ell}{\rho_i} = \frac{\min\{\rho_i, L\} - \ell}{\rho_i}, \qquad \rho_i > \ell. \tag{41}$$

Each extra dollar produces at least $\frac{y}{\bar{\rho}} - R$ of surplus. Integrating these gains over isolated shocks gives the lower bound

$$np(1-p)^{n-1}\left(\frac{y}{\bar{\rho}} - R\right)\int_{\ell}^{\min\{L,\bar{\rho}\}}[1 - F(\rho)]\,\mathrm{d}\rho. \tag{42}$$

The gains in all other states are nonnegative.

The added bankruptcy loss is confined to states with $k \geq 2$. In a one-shock state, expanded-contract net worth is

$$(y-\Delta)(n-1) + \Big[(y-\Delta) - R\rho_i\Big]x_i - Rn \;\geq\; n(y-\Delta) - R(n+\bar{\rho}) \;>\; 0, \tag{43}$$

where the first inequality follows because the coefficient of x_i is negative by Assumption 1, and the second is (28). Thus the BDC remains solvent in one-shock states. A new default that occurs under the increased firm credit limit from ℓ to $\overline{\rho}$ therefore requires a shock in $(\ell, \bar{\rho}]$ and at least one other shocked firm. Once the bank credit limit binds, draws remain L and continuation weakly increases, so no new default arises. Before it binds,

$$\frac{\partial \Pi(\boldsymbol{\rho}; \rho, L)}{\partial \rho} = \sum_{\rho_i > \rho}\left(\frac{R_N}{\rho_i} - R\right) \leq 0. \tag{44}$$

Each additional draw reduces net worth by less than R per dollar. For each drawing firm i, choose another shocked firm j independently of shock sizes. Given that j is shocked, its shock size remains uniform when all other firms' shocks are held fixed, and

$$-\frac{\partial \Pi}{\partial \rho_j} = \begin{cases} R, & \rho_j < \rho, \\ \frac{R_N \rho}{\rho_j^2}, & \rho_j > \rho, \end{cases} \qquad -\frac{\partial \Pi}{\partial \rho_j} \geq \frac{R_N \rho}{\bar{\rho}^2}. \tag{45}$$

Net worth decreases and draws increase with ρ_j, so the BDC crosses into bankruptcy at most once before the bank credit limit binds. The slope bound and uniform density bound

the probability near bankruptcy, per dollar of net worth, by $\frac{\bar{\rho}^2}{R_N \underline{\rho}(\bar{\rho}-\underline{\rho})}$. Hence,

$$\begin{aligned}
&\Pr(\Pi(\boldsymbol{\rho};\bar{\rho},L)<0)-\Pr(\Pi(\boldsymbol{\rho};\ell,L)<0)\\
&\leq n\ \underbrace{p[1-(1-p)^{n-1}]}_{\text{firm } i \text{ and another shocked}}\underbrace{\int_{\ell}^{\min\{L,\bar{\rho}\}}[1-F(\rho)]\,\mathrm{d}\rho}_{\text{draw}}\ \underbrace{\frac{R\bar{\rho}^2}{R_N\underline{\rho}(\bar{\rho}-\underline{\rho})}}_{\text{bankruptcy bound}}\ .
\end{aligned} \tag{46}$$

Combining the lower bound expected gain with the loss bound (46) yields

$$\begin{aligned}
&V(\bar{\rho},L)-V(\ell,L)\\
&\geq np\int_{\ell}^{\min\{L,\bar{\rho}\}}[1-F(\rho)]\,\mathrm{d}\rho\Bigg[\left(\frac{y}{\bar{\rho}}-R\right)(1-p)^{n-1}\\
&\qquad\qquad -n\lambda\frac{R\bar{\rho}^2}{R_N\underline{\rho}(\bar{\rho}-\underline{\rho})}[1-(1-p)^{n-1}]\Bigg]>0.
\end{aligned} \tag{47}$$

where the bracket term is positive under (29). This establishes that an optimum can be represented by full firm credit lines ($\ell^*=\bar{\rho}$) with a strictly positive bank credit line; if $\ell \geq L$, increasing ℓ leaves the allocation unchanged.

Part (ii), Step 3: partial bank credit line. Under $\lambda > \hat{\lambda}$ (31), full insurance $(\bar{\rho}, n\bar{\rho})$ is dominated by the contract $(\bar{\rho},\bar{\rho})$ and is therefore not optimal:

$$\begin{aligned}
&V(\bar{\rho},n\bar{\rho})-V(\bar{\rho},\bar{\rho})\\
&=\mathbb{E}\left[\sum_{\rho_i>0}(y-R\rho_i)\{1-x_i(\bar{\rho},\bar{\rho})\}\right]-n\lambda\left[\Pr(\Pi(\boldsymbol{\rho};\bar{\rho},n\bar{\rho})<0)-\Pr(\Pi(\boldsymbol{\rho};\bar{\rho},\bar{\rho})<0)\right]<0,
\end{aligned} \tag{48}$$

where the first term is the continuation surplus forgone at $(\bar{\rho},\bar{\rho})$ and the sign follows from the definition of $\hat{\lambda}$ in (31). Steps 1 and 2 establish a strictly positive bank credit limit and an allocation-equivalent representation with $\ell^*=\bar{\rho}$ for every joint optimum, giving $0<L^*<n\ell^*$. Any optimal representation with $\ell^*<\bar{\rho}$ must instead have $L^*\leq\ell^*$ by Step 2, so it also has $L^*<n\ell^*$. This proves part (ii). □

A.3 Two-Firm Example

This example spells out the exact marginal values that determine the optimal limits. Set $n = 2$ and $R_N = y - \Delta$. Extend F by zero below $\underline{\rho}$ and by one above $\bar{\rho}$. By Lemma A.4, specializing the reduced problem (27) to $n = 2$, the optimal limits maximize the payoff

$$\begin{aligned} V(\ell, L) = {} & 2p \int_{\underline{\rho}}^{\bar{\rho}} (y - R\rho_1) \min\left\{1, \frac{\ell}{\rho_1}, \frac{L}{\rho_1}\right\} [1 - pF(\rho_1)] \, \mathrm{d}F(\rho_1) \\ & + 2p^2 \int_{\underline{\rho}}^{\bar{\rho}} \int_{\rho_1}^{\bar{\rho}} (y - R\rho_2) \min\left\{1, \frac{\ell}{\rho_2}, \frac{\max\{L - \min\{\rho_1, \ell\}, 0\}}{\rho_2}\right\} \mathrm{d}F(\rho_2) \, \mathrm{d}F(\rho_1) \\ & - 2\lambda \Pr(\Pi < 0). \end{aligned} \tag{49}$$

BDC net worth under no shock, one shock with $\rho_i > 0 = \rho_j$, and two shocks satisfies

$$\begin{aligned} \Pi(0, 0) &= 2(R_N - R), \\ \Pi(\rho_i, 0) &= R_N - 2R + (R_N - R\rho_i)x_i, \\ \Pi(\rho_1, \rho_2) &= -2R + \sum_{i=1}^{2} (R_N - R\rho_i)x_i < 0. \end{aligned} \tag{50}$$

The one-shock state is where the contract matters: with no shock the BDC is always solvent, while with two shocks it always defaults—each funded unit adds bank debt $R\rho_i$ against collections $R_N < R\rho_i$, and no unshocked repayment remains to absorb the loss.

We restrict attention to a parameter region stated in primitives:

$$2R < R_N < \frac{R(2 + \bar{\rho})}{2}. \tag{51}$$

The chain keeps a lone shock survivable when unfunded ($R_N > 2R$) yet fatal when large and fully funded ($\frac{2R_N}{R} - 2 < \bar{\rho}$). Here $\frac{R_N - 2R}{R\bar{\rho} - R_N}$ is the funding fraction at which a lone largest draw exhausts net worth (50).

Firm credit limit. Suppose only one firm is shocked and has shock ρ, funded at $x = \min\left\{1, \frac{\ell}{\rho}, \frac{L}{\rho}\right\}$. Net worth (50) falls as the lone shock grows, with default threshold $\hat{\rho}(\min\{\ell, L\})$, where, on the interior branch,

$$\hat{\rho}(L) = \frac{R_N L}{R(L + 2) - R_N}, \tag{52}$$

for $\frac{R_N}{R} - 2 < L < \frac{2R_N}{R} - 2$. Below this range set $\hat{\rho}(L) = +\infty$; above it set $\hat{\rho}(L) = \frac{2R_N}{R} - 2$. A lone shock below the threshold leaves the BDC solvent; a lone shock above it triggers default, so the default probability is $p^2 + 2p(1-p)[1 - F(\hat{\rho}(\min\{\ell, L\}))]$. For $\frac{L}{2} < \ell < L$, differentiating (49) away from kinks gives

$$\begin{aligned}\frac{\partial V}{\partial \ell} = 2p \int_{\ell}^{\bar{\rho}} \left(\frac{y}{\rho} - R\right) [1 - 2pF(\rho) + pF(\ell) + pF(L-\ell)] \, \mathrm{d}F(\rho) \\ - 2\lambda \frac{\partial \Pr(\Pi < 0)}{\partial \ell}.\end{aligned} \tag{53}$$

For $\ell < L$, the default derivative is (55) with L replaced by ℓ, provided $\frac{R_N}{R} - 2 < \ell < \frac{2R_N}{R} - 2$ and $\underline{\rho} < \hat{\rho}(\ell) < \bar{\rho}$; otherwise it is zero away from kinks. At $L = 2\ell$, use the feasible one-sided derivative.

The marginal value of the firm credit limit trades the continuation surplus of additional draws against the bankruptcy risk they create in one-shock states. If $L \leq \ell$, increasing ℓ leaves the allocation unchanged, so we can set $\ell = \bar{\rho}$. For $\ell < L$, the sign depends on the two marginal values above.

Bank credit limit. Raising L funds the lone draw more deeply when $L < \ell$ and, in two-shock states, extends the larger draw once the smaller receives its permitted draw. The productive part of the derivative with respect to the bank credit limit is

$$\begin{aligned}2p\mathbf{1}\{L < \ell\} \int_{\max\{\underline{\rho}, L\}}^{\bar{\rho}} \left(\frac{y}{\rho} - R\right) [1 - pF(\rho)] \, \mathrm{d}F(\rho) \\ + 2p^2 \int_{\underline{\rho}}^{\bar{\rho}} \int_{\rho_1}^{\bar{\rho}} \left(\frac{y}{\rho_2} - R\right) \mathbf{1}\{0 < L - \min\{\rho_1, \ell\} < \min\{\rho_2, \ell\}\} \, \mathrm{d}F(\rho_2) \, \mathrm{d}F(\rho_1).\end{aligned} \tag{54}$$

The first term is the gain from funding the only or smaller draw; the second, from funding the larger draw once the smaller one receives its permitted draw. Integrals over empty intervals are zero. At the same time, a higher L, when $L < \ell$, lowers the default cutoff $\hat{\rho}(L)$, creating one-shock defaults at the margin: when $L < \ell$, $\frac{R_N}{R} - 2 < L < \frac{2R_N}{R} - 2$, and $\underline{\rho} < \hat{\rho}(L) < \bar{\rho}$,

$$\frac{\partial \Pr(\Pi < 0)}{\partial L} = 2p(1-p) F'(\hat{\rho}(L)) \frac{R_N(R_N - 2R)}{[R(L+2) - R_N]^2}, \tag{55}$$

and zero on the other smooth branches, including $L > \ell$.

A.4 Firm Liquidity Management

Hold the contracted limits, continuation rule, rate, and both fees fixed before firms choose unobserved liquidity-management effort. Firm i chooses p_i at increasing, strictly convex effort cost $c(1-p_i)$. The premium was priced at anticipated equilibrium behavior but cannot adjust to an unobserved deviation. Maintain the baseline treatment of firm bankruptcy as a social cost. Define coverage as the expected continuation fraction conditional on a shock:

$$\gamma_i(\ell, L; p_{-i}) = \mathbb{E}[x_i(\ell, L) \mid \rho_i > 0]. \tag{56}$$

The positive-shock size distribution is unchanged by effort. Independence makes γ_i independent of p_i. Couple other firms' shock sizes while switching firm i from unshocked to shocked. An additional request cannot raise another firm's allocation under smallest-first priority. Accordingly,

$$\frac{\partial \gamma_j(\ell, L; p_{-j})}{\partial p_i} \leq 0 \qquad (j \neq i). \tag{57}$$

The inequality is strict when firm i's request displaces firm j's continuation with positive probability. It is zero when the bank credit line funds all covered requests in full.

Ignoring the fixed premium, firm i maximizes

$$(1 - p_i)(y - R_N) + p_i \Delta\gamma_i - c(1 - p_i). \tag{58}$$

An interior choice satisfies

$$c'(1 - p_i) = (y - R_N) - \Delta\gamma_i. \tag{59}$$

A planner maximizing these firms' joint payoffs, holding the same insurance contract fixed, instead has the marginal condition

$$c'(1 - p_i) = (y - R_N) - \Delta\gamma_i - \Delta \sum_{j \neq i} p_j \frac{\partial \gamma_j}{\partial p_i}. \tag{60}$$

The final term is nonnegative and strictly positive when there is displacement.

Proposition 2. *At fixed insurance terms, a firm's private marginal benefit from liquidity management is no greater than its marginal contribution to the joint payoff of insured firms. The difference is strictly positive when its draw crowds out another firm's continuation with*

positive probability. This congestion wedge vanishes under a full bank credit line.

These conditions compare incentives at a common exposure vector. If the entrepreneur also bears its own bankruptcy cost, λ enters both right-hand sides equally and leaves the congestion wedge unchanged. The planner here aggregates insured firms' payoffs only. A social planner must also include changes in lender collections, the opportunity cost of funds, and bankruptcy losses. If effort were contractible before pricing, both premiums and the bank fee could respond. Neither partial backing nor this borrower wedge alone establishes a global ordering of market and socially optimal effort.

Internet Appendix

"Credit Commitments by Nonbanks"

IA.1. Data Collection and Processing

This section provides details on sample construction. Section IA.1.1 defines the universe of BDCs and their regulatory filings. Sections IA.1.2–IA.1.5 describe each group of variables collected from those filings: total unfunded commitments, unfunded amounts in commitment books, bank credit lines, balance-sheet items, and statement-of-cash-flow items. Section IA.1.6 describes the linking of borrowers in BDC commitment books to PitchBook companies. Section IA.1.8 describes the FFIEC Call Report data on banks.

IA.1.1. Universe of BDCs from SEC EDGAR

We identify the universe of BDCs from the SEC's EDGAR system based on Form N-54A, N-54B, and N-54C filings, which respectively elect, amend, and withdraw BDC status under the Investment Company Act of 1940. The BDC universe over our sample period (2005Q1–2025Q4) consists of all entities with an active N-54A election in any given quarter. The SEC's annual list of BDCs is used to discover CIKs but is incomplete as a status authority, so we additionally filter on N-54A/N-54C dates: 225 CIK-quarter filings from 11 entities are removed because they fall after a recorded N-54C withdrawal (so the entity had ceased to be a BDC at the time of the filing), and 12 CIKs that appear on SEC lists with no corresponding 10-K/10-Q filings are dropped. We also exclude a BDC-quarter if the filings indicate that the BDC had not begun investment operations, determined by the first portfolio investment or binding obligation to invest. The cleaned list of filings contains 6,747 CIK-quarter filings across 245 unique BDCs spanning 2005Q1–2025Q4. For each CIK-quarter in this roster we

collect the 10-K or 10-Q filing from EDGAR's full-text search index; these filings are the source for the variables described in Sections IA.1.2–IA.1.5 below.

Within this universe, we further distinguish BDCs by exchange-listing status: Listed BDCs (file Form 8-A12B and trade on exchanges) and non-listed BDCs (file periodic reports under Section 15(d) or 12(g) but are not listed on a national exchange). Listing status is assigned by matching each filing to the most recent Form 8-A registration or Form 15 deregistration event on the CIK. Figure IA.1 shows the growth of the two listing-status groups by count and aggregate total assets. The exchange-listed segment grew from 2 BDCs in 2005Q1 to roughly 50 by the mid-2010s and has been stable since, with aggregate total assets rising from near zero to about $180 billion by 2025Q4. The non-listed segment grew modestly through the 2010s but expanded sharply from 2020Q1 onward, reaching about 100 BDCs and roughly $370 billion in aggregate total assets by 2025Q4, which reflects the recent proliferation of perpetual non-traded BDCs raising capital through registered public offerings. The two segments combined now manage roughly $550 billion of total assets.

IA.1.2. BDC-Level Total Unfunded Commitments

During our sample period, nearly all BDCs disclose in their 10-K/10-Q the aggregate dollar value of unfunded loan commitments to portfolio companies, typically in the commitments-and-contingencies footnote or the management discussion section. We manually collect this filing-level total amount for each CIK-quarter. In the process, we ensure it is not confused with undrawn credit limits of bank credit lines in which the BDC is a borrower.

IA.1.3. Unfunded Amount in Commitment Books

A subset of BDC-quarters disclose a table (or list) of the BDC's unfunded commitments to each portfolio company, typically in the same commitments-and-contingencies note as the

total amount. We collect each borrower's unfunded amount and commitment type (e.g., revolving credit facility, delayed-draw term loan), along with the corresponding outstanding loan principal where reported. For quality control, we validate the sum of unfunded amounts within a book against the BDC's reported total unfunded commitments (Section IA.1.2). The dataset we collect covers 3,749 BDC-quarters and 167,389 facility-level observations within our 2005Q1–2025Q4 sample window.

IA.1.4. BDCs' Bank Credit Lines

BDCs' 10-K and 10-Q filings discuss each bank credit facility the BDC has as a borrower in a dedicated borrowings note. The note typically gives, for each active facility at the filing date, the facility name, the lender name (the administrative agent and other lenders if syndicated), the credit limit, the drawn balance, the undrawn capacity, the maturity date, the interest-rate terms (benchmark and spread), and any contractually specified accordion provision (borrower's option to increase credit limit). Discrete changes to a facility during the quarter—origination of a new facility, amendment to an existing facility, exercise of an accordion, termination, or replacement—are reported in the same note, generally as narrative text linked to the facility name.

We assign a unique credit line identifier (CLID) to each bank credit facility a BDC discloses. The CLID identifies a facility across time, even if the facility experiences changes at different filing dates across quarters. Sub-facilities of an SPV credit structure that are disclosed under separate names with separate limits are each given their own CLID. Renamings of the same facility (e.g., after a replacement of the administrative agent) are kept on the same CLID with an event flag for the rename. For each CLID-quarter pair, we record the values of the variables observed in the filing at that date: credit limit, drawn balance, undrawn capacity, maturity date, administrative agent, other syndicate lenders, interest-rate bench-

mark, spread, and any accordion provision. The resulting panel covers 9,118 CLID-quarter rows across 776 unique CLIDs and 200 BDCs spanning 2005Q1–2025Q4.

We record events from two complementary sources. The inceptions and terminations of CLIDs are derived directly from the CLID-quarter panel: the inception of a CLID is the first quarter in which that CLID appears, and the termination is the last quarter in which the CLID appears (excluding the sample end). Amendments and accordion exercises, which change the value of a variable on an existing CLID without changing CLID identity, are extracted from the same borrowings note as the variables: each disclosed change is recorded as a separate event with the event type (amendment, accordion exercise, replacement of admin agent, etc.), the changed field (limit, maturity, spread, etc.), and the pre- and post-change values.

IA.1.5. Balance Sheet and Cash Flow Statement Items

We collect each BDC's balance-sheet items, including total assets, total liabilities, total equity, total debt, and cash and equivalents, from the 10-K/10-Q filings. We supplement with Compustat and S&P Capital IQ data on the same CIK and quarter and use them to cross-validate against the filing-derived values.

We also collect statement-of-cash-flow (StoCF) data from the filings. Seven items are extracted: the three category subtotals (net operating, investing, and financing cash flows) and four line items (gross investment purchases, gross investment sales and repayments, distributions paid, and equity issuance). This cash flow dataset covers 6,294 BDC-quarter rows across 242 BDCs spanning 2005Q1–2025Q4.

IA.1.6. Identifying Borrowers in Commitment Books

The commitment book data in Section IA.1.3 include borrower *names*. However, without a unique identifier, we cannot (i) track each borrower across quarters and BDCs and align the unfunded commitment book with the BDC's on-balance-sheet portfolio holdings, and (ii) merge in firm characteristics (industry, state, age, sponsor backing) for the analyses. We use PitchBook's company identifier for this. To do so, a challenge is that PitchBook tracks borrowers by parent/operating company, while filings disclose the specific borrowing entity—often an SPV, intermediate holdco, or acquisition shell ("ABC Buyer, Inc." rather than "ABC Corp"). Direct name matching fails on a significant share of borrowers even when the underlying firm is covered by PitchBook.

Our linking strategy uses FactSet's BDC portfolio holdings data as a bridge. FactSet records each holding under the original borrowing-entity name from the EDGAR filing, so the EDGAR name and the FactSet name are near-identical. FactSet also reports the instrument-level terms (par value, maturity, base rate, spread) for each holding, and PitchBook reports the same instrument-level terms under its own parent-keyed company identifier. For each holding position, we match the FactSet record to a PitchBook record on the instrument's par value, maturity, base rate, and spread, which works precisely because it identifies the same loan from the SPV side (FactSet) and the parent side (PitchBook). The PitchBook identifier from the matched holding is then carried back onto the corresponding borrower name in the commitment book. For the remaining unmatched borrowers, we apply a within-CIK name matching to PitchBook. The combined procedure identifies 84–87% of unique borrower names.

IA.1.7. Uncalled Investor Capital Commitments

A subset of BDC-quarters, typically unlisted BDCs during their earlier periods, have access to uncalled capital committed by their limited partners ("dry powder"). We collect data on this dry powder from BDCs' 10-K and 10-Q filings. If the BDC reports an amount of uncalled investor commitments, we directly use that value. If the BDC discloses historical investor commitments and capital call activity, we reconstruct the dry powder from these values. If the BDC discloses neither such information, we treat the dry powder as zero.

IA.1.8. Bank Data from FFIEC Call Reports

We obtain data on banks from the FFIEC's Consolidated Reports of Condition and Income (Call Reports). We extract balance-sheet items (Schedule RC), loans and leases by category (RC-C Part I), and off-balance-sheet unused commitments (RC-L) for each bank-quarter. The unused-commitment items require one reconciliation: in December 2024 the FFIEC retired the combined financial-institution unused-commitment line (`RCFDJ458`) and replaced it with separate depository (`PV10`) and nondepository (`PV11`) components starting 2024Q4. For a time-stable measure we use `RCFDJ458` prior to the revision and `PV10` + `PV11` thereafter, and we expose `PV11` separately for analyses that need to isolate nondepository (BDC-relevant) from interbank commitments.

IA.2. Measurement of Credit Facility Drawdown

IA.2.1. Borrower Drawdown in BDC Unfunded Commitment Books

Our sample of BDC unfunded commitment books consists of continuing facilities, defined as positions present in both $t-1$ and t in the same combination of BDC-borrower-commitment type. This filter excludes originations and terminations of credit facilities, which would

otherwise mechanically inflate $\%\Delta Unfunded$ or generate $\%\Delta Unfunded = -1$. We additionally restrict the sample to BDC-borrower-quarters with lagged unfunded commitment above \$1 million. The restriction avoids small-denominator noise in $\%\Delta Unfunded$. The threshold matches the analogous filter applied to S&P Capital IQ public-firm drawdowns in Section IA.2.2.

We measure the borrower's liquidity shock with two alternative measures. The continuous shock is the negative of the percentage change in unfunded commitment, $-\%\Delta Unfunded_{i,\ell,t} = -\Delta Unfunded_{i,\ell,t}/Unfunded_{i,\ell,t-1}$, winsorized at the 1st and 99th percentiles, so that positive values indicate drawdowns. The binary shock is the indicator $\mathbf{1}\{Unfunded_{i,\ell,t} < 0\}$. The continuous measure helps quantify the magnitude of drawdown, while the binary measure is robust to the outlier tail that the continuous measure inherits and is more interpretable as the fraction of borrowers actively drawing down their commitment.

The interpretation of $\Delta Unfunded$ requires care because changes in unfunded commitment can come from two sources: (i) borrower drawdowns and repayments; (ii) amendments to the total committed amount. Because the BDC's total commitment to a borrower is not consistently reported in 10Q and 10K filings, we cannot always separately identify the two sources of change in unfunded commitment. However, in a subsample where the total commitment is reported (15 BDCs, 5,212 BDC-borrower-quarters), we find that source (ii) is infrequent: amendments to the total commitment occur in only 21.7% of BDC-borrower-quarter observations, suggesting that $\Delta Unfunded$ is a reasonable proxy for borrower drawdown activity. Figure IA.5 shows that when the total commitment is unchanged between two consecutive quarters (78.3% of observations), the accounting identity $\Delta Unfunded = -\Delta$funded holds exactly, with a sample correlation of -1.000.

IA.2.2. Public-Firm Drawdown Factors from S&P Capital IQ

Regressions in Table 6 use aggregate drawdown factors constructed from S&P Capital IQ (CIQ) Capital Structure data merged with the Compustat quarterly database. The sample is non-financial Compustat firms (SIC outside 6000–6999) over 2010Q1–2024Q4, restricted to firm-quarters with lagged credit-line drawn balance above $1 million. This yields approximately 79,000 firm-quarters across around 4,600 unique firms. For each firm-quarter, we measure drawdown as the percentage change in outstanding credit line drawn amount, winsorized at the 1st and 99th percentiles. We use change in drawn rather than change in unfunded because CIQ does not consistently report credit limits, particularly in fourth-fiscal quarters. We then stratify firms by their lagged Debt-to-EBITDA ratio (i.e., the sum of long-term and current-portion long-term debt, divided by trailing-four-quarter EBITDA) into four buckets ($[0, 2)$, $[2, 4)$, ≥ 4, and a negative-EBITDA bucket). For each bucket and quarter, we compute the average drawdown weighted by lagged drawn balance. The resulting four quarterly time series are the factors used in columns 1–4 of Table 6, Panel A.

IA.3. Specialization and Selection in BDC Commitments

This section provides evidence consistent with BDCs selectively extending commitments based on their information advantages.

IA.3.1. Specialization in Borrower Segments

BDCs may deliberately overweight industries, geographies, or sponsor relationships for which they have better information. Following Blickle, Parlatore, and Saunders (2026), we compute each BDC-quarter's weight in a borrower industry, state, or sponsor bucket in excess of the cross-BDC aggregate, separately for commitment books and portfolio holdings. Table IA.3 shows that at the industry level, the median BDC's largest excess share is 25 pp for commit-

ment books versus 12 pp for portfolio holdings, and the cumulative excess share across the top three industries is 44 pp versus 25 pp. The same pattern holds for borrower geography (22 pp versus 8 pp for Top-1 and 42 pp versus 17 pp for Top-3) and sponsor relationships (27 pp versus 9 pp for Top-1 and 55 pp versus 21 pp for Top-3), with all differences significant at the 1% level. This result suggests that BDCs extend commitments to borrowers for which they have superior screening or monitoring capacity.

IA.3.2. Within-Segment Selection of Borrowers

Beyond specialization in borrower segments, BDCs may also selectively extend commitments to borrowers within a given industry and geography. To investigate this selection, we regress an indicator for whether a BDC extends an unfunded commitment to an existing borrower on its firm characteristics and relationship with the BDC. To account for industry and geographical heterogeneities and time-varying BDC-specific effects, our regressions include industry-by-quarter, HQ-state-by-quarter, and BDC-by-quarter fixed effects.

Table IA.4 reports the estimation results. A strong predictor of the extension of a commitment is the borrower's credit quality, implying that the BDC selectively extends commitments to borrowers with lower default risk.[1] Sponsor backing adds 4.6 pp to the probability, consistent with evidence that sponsor engagement can substitute for lender monitoring (Haque, Mayer, and Wang, 2026). The Dual Held indicator adds 2.5 pp, and this relationship is concentrated in revolvers, consistent with evidence that BDC dual holders are compensated for monitoring and governance services (Davydiuk, Erel, Jiang, and Marchuk, 2025). Recent M&A activity adds another 5.5 pp to the probability, and its association is stronger on DDTLs, which are typically used for acquisition financing. Moreover, smaller and younger borrowers are more likely to receive commitments, and the BDC's larger existing exposure

[1] We measure credit quality at the borrower-quarter level using the lagged cost-weighted average fair-value-to-cost ratio across all BDCs' term-loan holdings of the borrower.

to the borrower also positively predicts commitment extension.

Overall, these findings suggest that BDCs selectively extend commitments based on private information, borrower needs, and risk considerations, contributing to the concentration of BDC commitment books.

IA.4. Bank Credit Lines: Composition, Events, and Robustness

This appendix documents the bank credit line data underlying Section 2.3 and reports a robustness test of the backstop interpretation. Our data on credit-agreement details (i.e., lenders, credit limits, drawn balances, maturities, spreads, and accordion provisions) cover a panel of 9,118 CLID-quarter observations across 776 credit lines and 200 BDCs.

Table IA.5 summarizes the lenders that provide these credit lines. After standardizing lender names and merging bank-holding-company broker-dealers into their parent type, US and foreign banks together provide the vast majority of credit lines to BDCs. The administrative-agent role is concentrated among a small set of large banks, led by JPMorgan, Deutsche Bank, and Citibank. Figure IA.6 plots the composition of administrative agents by lender type at annual frequency over 2005–2025, showing that the predominance of bank lenders has persisted throughout the sample period.

Figure IA.7 shows the annual number of contractual events on these facilities between 2005–2025: of 6,584 events, amendments are the most common, followed by inceptions of new facilities. Table IA.6 reports detailed composition of these events: amendments are overwhelmingly upsize credit limits and extend maturities. Table IA.7 documents the accordion feature: about 30% of credit lines carry an accordion option that allows the BDC to upsize the facility without negotiating a new agreement, roughly half of those options are exercised at least once, and the median accordion cap sits about 14% above the base credit limit.

Finally, Table IA.2 reports a panel event study around the 2023 regional bank stress. We test whether BDCs with greater pre-shock exposure to US regional banks, or to administrative agents with low Tier-1 capital ratios, experience contraction in their bank credit line limits after 2022Q4. Across both treatment definitions and all time horizons, the estimated effects are statistically insignificant with flat pre-trends (the one marginally significant coefficient, at $t = +1$ for low-Tier-1 exposure, disappears once controls are added). This result shows that pre-committed revolving facilities remain in place even when the lending bank itself is under stress, supporting the liquidity backstop interpretation.

IA.5. Response of Bank Credit Lines to BDC Liquidity Needs

This appendix examines how BDCs' bank credit lines respond on the margin to BDC liquidity needs, complementing the descriptive backstop evidence in Section 2.3 of the paper. Ideally, we would measure borrower total drawdowns at the BDC-quarter level. However, we cannot cleanly measure this BDC-level total amount because changes in the total unfunded commitment are confounded by new originations and terminations, as well as amendments that increase or decrease the total commitment size.[2] Moreover, in the cash flow statement, borrower drawdowns on unfunded commitments are reported together with other investment activities under a single cash outflow item. We therefore use the BDC's gross investment cash outflow as a measure to capture liquidity needs the BDC faces in a given quarter. Table IA.8 illustrates the scale of borrower drawdowns in a concrete case: Ares Capital's commitment book around the 2020Q1 COVID stress. Panel C of the table shows the liability-side counterpart: Ares funded the wave in part by drawing $464 million across its three bank credit lines in 2020Q1, and by 2020Q2 it had repaid $786 million while expanding committed capacity

[2]The facility-level measure in Section 2.2 is not subject to this confounding: the sample is restricted to continuing facilities with at least $1M lagged unfunded (Internet Appendix IA.2.1), which isolates drawdown activity from origination and termination effects.

by about $560 million, including a newly originated $300 million facility.

Table IA.9 reports summary statistics for the variables used in this analysis. We estimate the association between the BDC's liquidity needs and its bank credit line activities. In column 1 of Table IA.10, we regress the amount of the BDC's bank credit line drawdown on its quarterly gross investment cash outflow, both scaled by lagged total assets. We control for the BDC's undrawn credit limit, total debt, cash and equivalents, and log total assets. The regression includes BDC fixed effects to account for time-invariant BDC-level heterogeneity and year-quarter fixed effects to absorb common time trends in bank liquidity provision. The coefficient on the gross investment cash outflow is positive and statistically significant, suggesting that a one-dollar increase in total liquidity needs is associated with 10 cents of drawdown on the BDC's existing bank credit lines.

In columns 2–4, we consider three other margins on which BDCs and banks adjust the credit lines. Column 2 examines amendments to existing facilities, where the dependent variable is the change in credit limit. Column 3 examines new facilities, where the dependent variable is the credit limit of newly originated facilities. The coefficient on the gross investment cash outflow is positive and statistically significant for both amendments and new originations. For each dollar of cash outflow, the BDC obtains 4 additional cents of existing facility limits and originates 6 cents of credit limits from new facilities. Column 4 examines the change in credit limit due to terminations of existing facilities, where the coefficient is small in magnitude and statistically insignificant. In total, the BDC expands its bank credit line capacity by 10 cents per dollar of incremental investment cash outflow.[3]

[3]A caveat is that we do not observe clean exogenous shocks to the BDC's liquidity needs. Hence, the estimates should be interpreted as associations driven by the BDC's investment and financing choices. Table IA.11 shows that the gross investment cash outflow is also positively associated with its cash inflows from other funding sources such as investment payoffs and equity issuance.

IA.6. Other Liquidity Sources

A BDC's other funding sources may affect the relationship between its undrawn bank credit and unfunded commitments, as well as our assessment of whether its total liquidity available is sufficient to meet borrower drawdowns. We examine a specific funding source, uncalled investor capital commitments, or "dry powder," which are concentrated among younger, unlisted BDCs (Figure IA.8). Dry powder may affect the estimated relationship in Table 7 through two opposing channels. On the one hand, BDCs with more dry powder may extend more commitments while needing less bank credit, creating a potential downward bias. On the other hand, dry powder may increase bank credit by serving as collateral or by generating demand for bridge financing around capital calls, potentially producing an upward bias.[4]

Table IA.12 repeats the regressions in Panel A of Table 7 using a subsample of BDC-quarters with zero lagged dry powder. This subsample accounts for 3,734 of the 4,699 BDC-quarters in the baseline regressions. The coefficients on total unfunded commitments are 0.391 for undrawn bank credit and 0.429 when cash is included. Both are positive and statistically significant, and both remain significantly below one. Our results thus remain similar among the majority of the baseline sample with zero lagged dry powder.

[4]As a funding source, dry powder may itself require a liquidity buffer: funds often use bank credit lines to bridge the time gap between their capital calls and LP cash transfers (Fitch Ratings, 2023; Stackhouse and Velez, 2026).

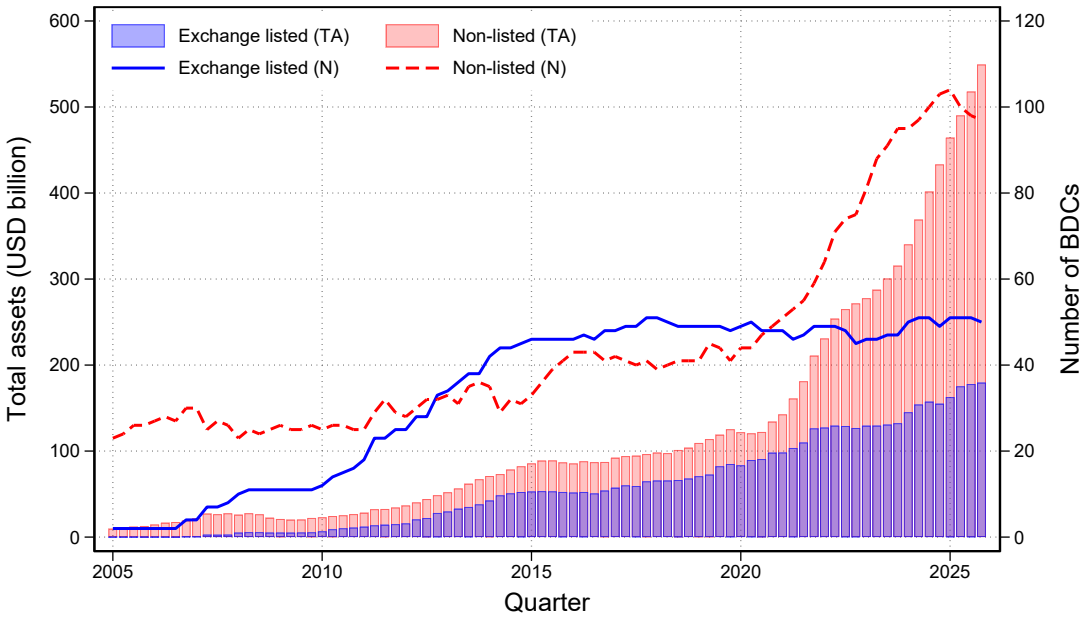
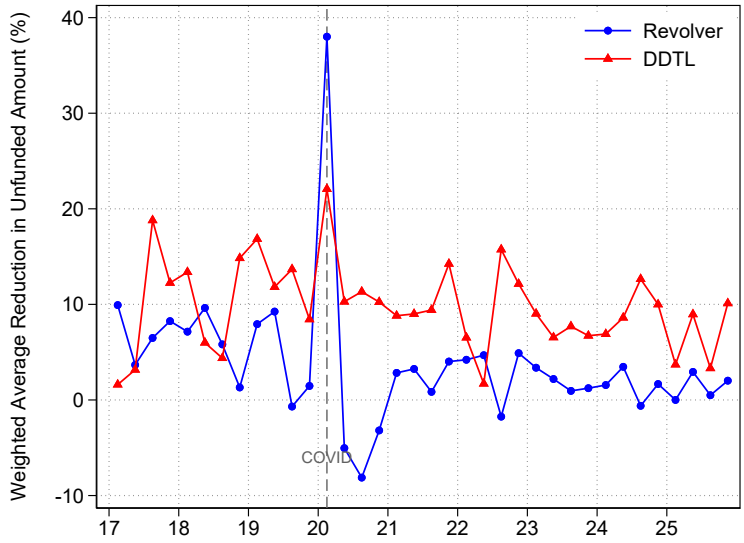


Figure IA.1. BDCs by Listing Status: Number and Total Assets.
This figure plots the BDC universe between 2005Q1 and 2025Q4 by listing status. The stacked bars (left axis) show total assets (USD billion) summed across BDCs in each segment per quarter, with exchange-listed BDCs at the bottom (blue) and non-listed BDCs stacked on top (red). The solid blue and dashed red lines (right axis) show the corresponding number of BDCs in each segment. Data source: SEC EDGAR.

(a) $-\%\Delta$Unfunded



(b) $\mathbf{1}(\Delta\text{Unfunded} < 0)$

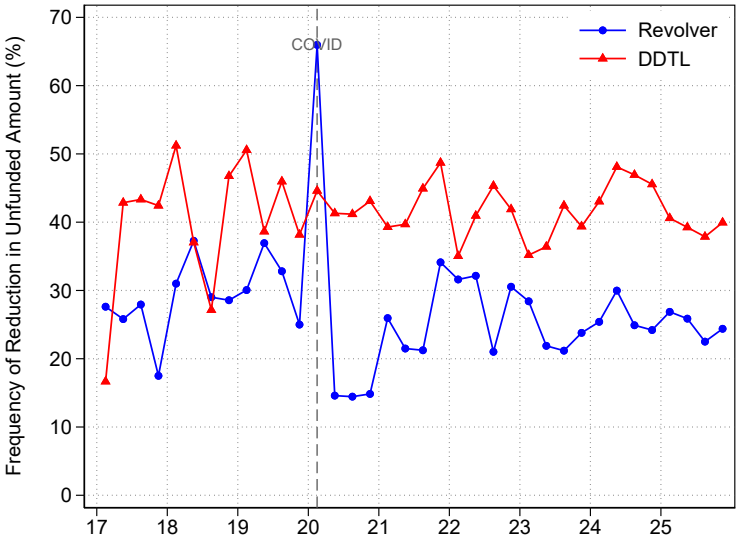


Figure IA.2. Changes in Unfunded Commitments by Commitment Type. This figure presents the time series of changes in unfunded commitments extended by BDCs to their borrowers from 2017Q1 to 2025Q4, categorized by commitment type (Revolver and DDTL). Panel (a) shows the average quarterly reduction in unfunded commitment amounts for each type, so that positive values indicate drawdowns. Panel (b) displays the quarterly frequency of reductions in unfunded commitment amounts. The vertical dashed line marks the onset of the COVID-19 pandemic.

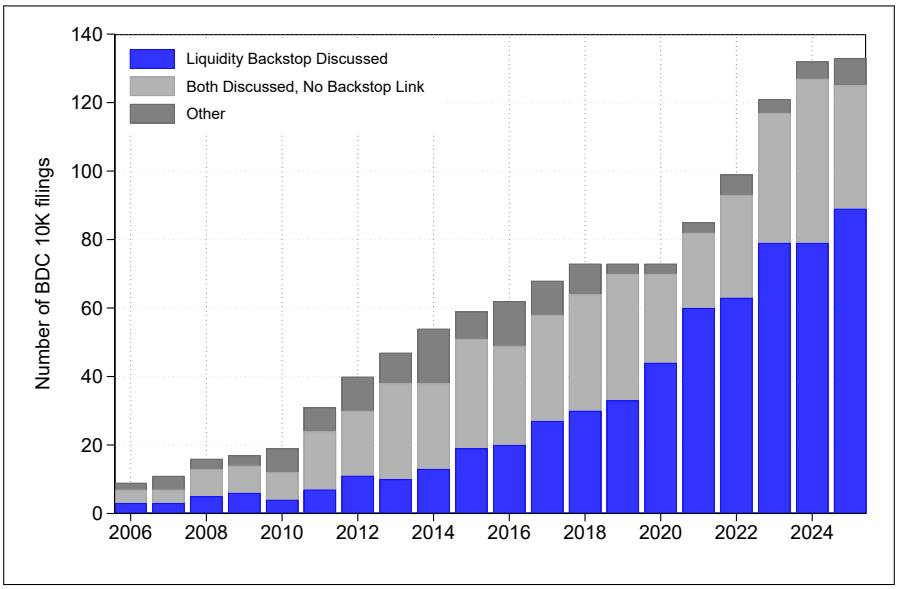


Figure IA.3. Disclosure of Liquidity-Backstop Discussion in BDC 10-K Filings. This figure plots the number of BDC 10-K filings in each year by disclosure status. The sample comprises 1,222 10-K filings from 2006 through 2025, each classified into one of three categories. "Liquidity Backstop Discussed" marks filings in which the BDC names at least one specific source of liquidity (e.g., cash, bank credit facility, marketable securities, LP capital commitments) as backstop for its unfunded commitments to portfolio companies. "Both Discussed, No Backstop Link" marks filings that discuss both the BDC's unfunded commitments and its liquidity sources without explicitly connecting the two, including filings that mention only generic-adequacy language (e.g., "adequate financial resources") without naming a specific source. "Other" includes filings with no relevant disclosure or where only one side (liquidity or commitments) is discussed.

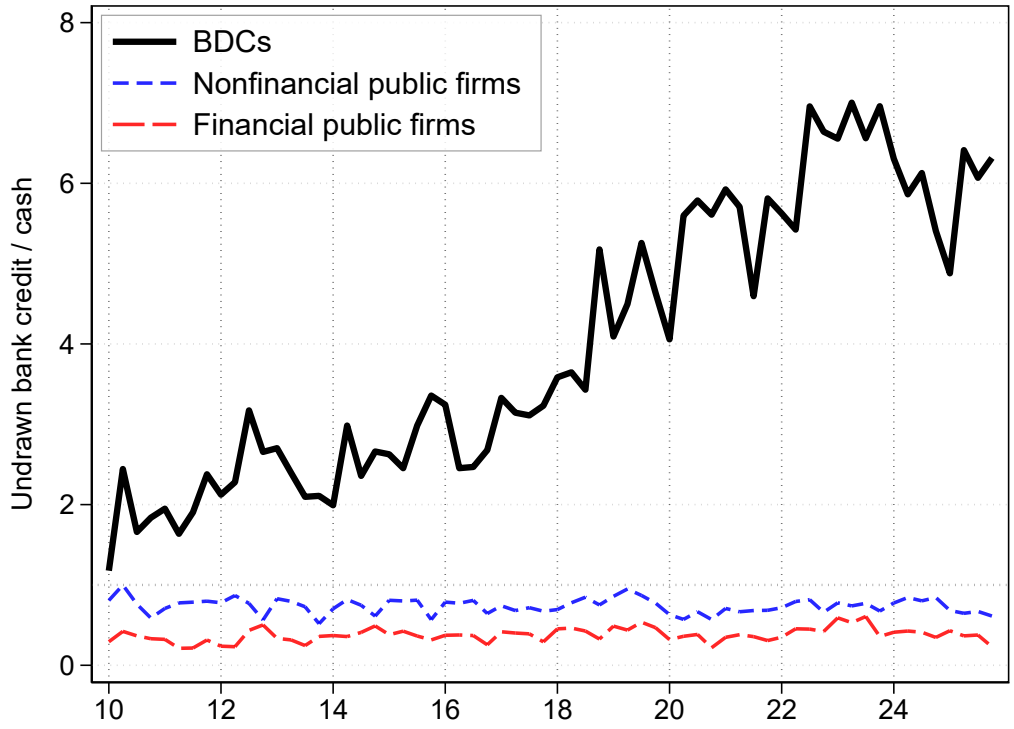


Figure IA.4. Undrawn Bank Credit to Cash Ratio: BDCs vs. Public Firms. This figure plots the quarterly aggregate ratio of undrawn bank credit line capacity to cash and cash equivalents, separately for the BDC sector, nonfinancial public firms (Compustat S&P Capital IQ, SIC outside 6000–6999), and financial public firms (SIC 6000–6999). Within each sector and quarter, the numerator is the sum of undrawn capacity across all firms that report a credit line limit, and the denominator is the sum of cash and cash equivalents across the same firms. Data sources: SEC's EDGAR (BDCs); S&P Capital IQ Capital Structure and Compustat quarterly (public firms).

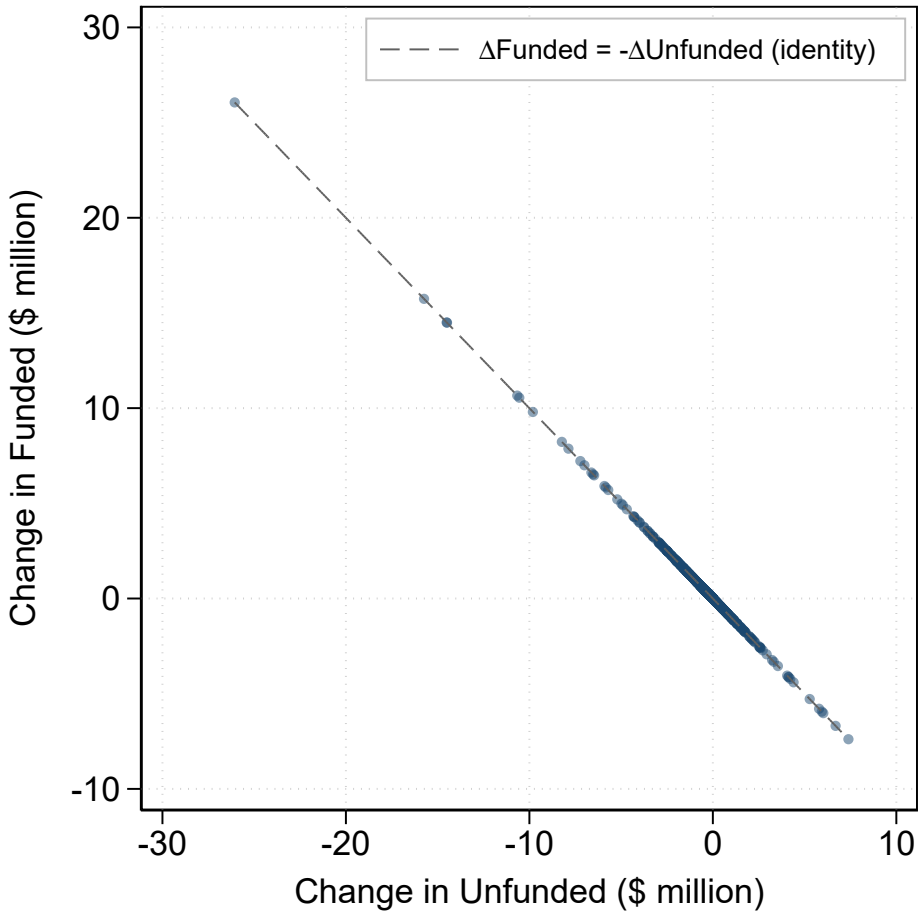


Figure IA.5. Change in Unfunded Commitment as a Proxy for Drawdown. This figure plots quarterly changes in unfunded commitments against changes in funded commitments at the BDC–portfolio company level, within the subsample where the BDC's total commitment to the borrower is unchanged between consecutive quarters (78.3% of observations). On this subsample, the accounting identity $\Delta\text{Funded} = -\Delta\text{Unfunded}$ holds by construction, and the points lie on the identity line with a sample correlation of -1.000. The sample is restricted to 15 BDCs (5,212 BDC-borrower-quarters) that report funded amounts for individual portfolio company commitments.

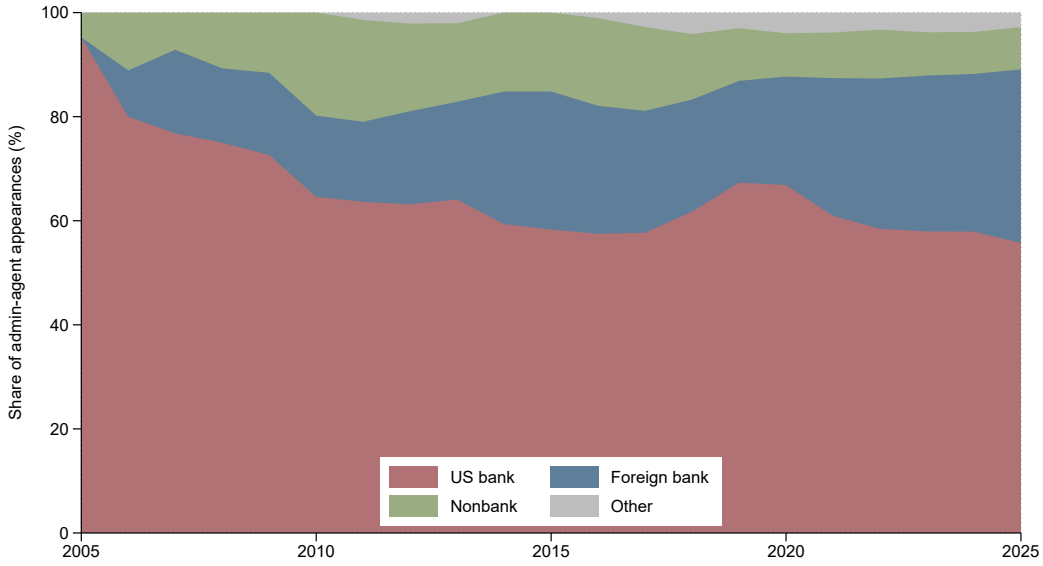


Figure IA.6. Composition of Admin Agents Over Time.
This figure plots the share of administrative agents on BDC credit lines by lender type at annual frequency over 2005–2025, as a stacked area chart. The four buckets match Table IA.5: US bank, Foreign bank (foreign-headquartered banks operating in the US through a domestic branch), Nonbank (independent nonbank lenders, asset managers, and insurance companies; SEC-registered broker-dealers are reclassified into the type of their parent), and Other (BDC investment-adviser affiliates, trust companies, and central-bank discount-window borrowings). Source: SEC's EDGAR (10-K and 10-Q filings).

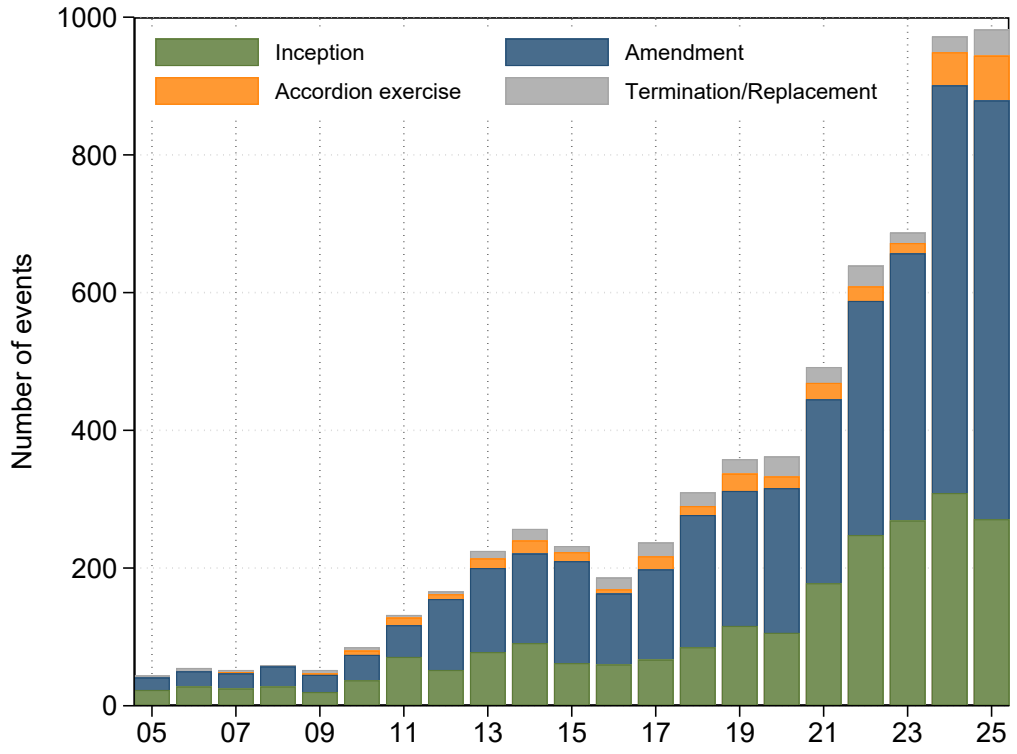


Figure IA.7. Bank Credit Line Events Over Time.
This figure plots the annual count of bank credit line events extracted from BDC 10-K and 10-Q filings, 2005–2025, stacked by event type: inception, amendment, accordion exercise, and termination/replacement (terminations and replacements are pooled). Source: SEC's EDGAR (10-K and 10-Q filings).

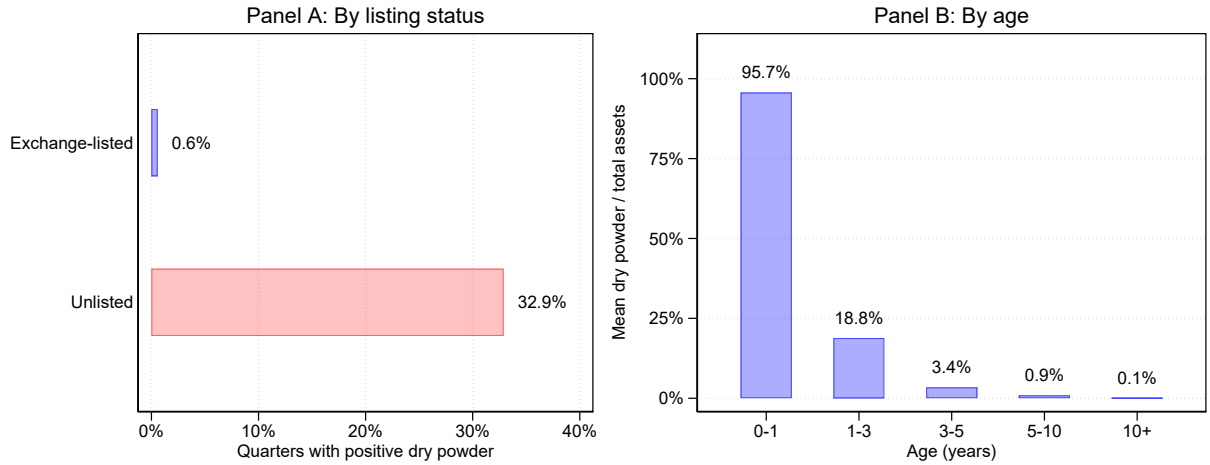


Figure IA.8. Investor Dry Powder by Listing Status and Age.
This figure summarizes investor dry powder for BDC-quarters between 2005Q1 and 2025Q4. Dry powder is uncalled investor capital committed to a BDC. Panel A reports the fraction of BDC-quarters with positive dry powder by listing status. Unlisted BDCs include public non-traded BDCs and private BDCs. Panel B reports the average dry powder to total assets ratio by BDC age. Age is measured by observed operating history: years since the BDC's first observed operating quarter. Data sources: SEC EDGAR and BDC investor materials.

Table IA.1. Volatility of BDC-Level Liquidity Shocks vs. a Diversified Benchmark

This table compares the volatility of BDC-level liquidity shocks from the commitment book against a diversified benchmark. The benchmark equal-weights all unfunded commitments extended to borrowers in the BDC universe. The sample consists of 79 BDCs with at least 12 quarters between 2005Q1 and 2025Q4 in which the BDC has at least 5 continuing borrowers in its commitment book. Two shock measures are reported. The continuous shock is the negative of the percentage change in unfunded commitment, $-\Delta Unfunded_{i,\ell,t}/Unfunded_{i,\ell,t-1}$, so that positive values indicate drawdowns. The binary shock is the indicator $\mathbf{1}\{\Delta Unfunded_{i,\ell,t} < 0\}$. For each BDC ℓ, μ_ℓ and σ_ℓ are the time-series mean and standard deviation of BDC ℓ's own shock series (dollar-weighted across its continuing borrowers in the continuous case, equal-weighted in the binary case). σ_ℓ^{BMK} is the time-series standard deviation of the diversified-benchmark shock computed over the same quarters as BDC ℓ. Each row reports the cross-sectional distribution across the 79 BDCs. The BDC-level volatility σ_ℓ feeds the magnitude estimates in Table 3 of the paper.

	$-\%\Delta$Unfunded				$\mathbf{1}(\Delta\text{Unfunded} < 0)$			
	μ_ℓ (1)	σ_ℓ (2)	σ_ℓ^{BMK} (3)	$\sigma_\ell/\sigma_\ell^{\text{BMK}}$ (4)	μ_ℓ (5)	σ_ℓ (6)	σ_ℓ^{BMK} (7)	$\sigma_\ell/\sigma_\ell^{\text{BMK}}$ (8)
mean	0.077	0.122	0.040	3.439	0.375	0.137	0.051	3.221
p25	0.049	0.080	0.027	2.153	0.316	0.112	0.027	2.005
p50	0.077	0.103	0.035	2.683	0.381	0.131	0.057	2.589
p75	0.102	0.140	0.052	3.694	0.441	0.156	0.067	4.217

Table IA.2. BDCs' Bank Credit Limit Around the 2023 Banking Crisis

This table reports a panel event-study test of bank credit line backstop stickiness around the 2023 banking stress. The sample is a BDC × quarter panel of 90 BDCs with at least one identified bank credit-line administrative agent at 2022Q4, observed at horizons $t = -4, \ldots, +4$ relative to 2022Q4. The dependent variable is log(Credit Limit$_{\ell,t}$). Columns 1–2 use *RegionalExposure* as the continuous treatment, defined as the BDC's pre-shock dollar credit limit at US-regional-bank admin agents scaled by 2022Q4 total assets; columns 3–4 use *LowTier1Exposure*, the analogous limit-weighted exposure to admin agents whose Tier-1 RBC ratio at 2022Q4 falls in the bottom quartile of the admin-bank universe (cutoff 10.64%, from FFIEC Call Report Schedule RC-R). Columns 2 and 4 add horizon-interacted balance-sheet controls used in Tables 7 and IA.10: pre-shock log(TA), Debt/TA, and Cash/TA. All specifications include BDC and year-quarter fixed effects with the reference horizon at $t = 0$, standard errors are clustered at the BDC level, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance. Eligibility is checked at the observation date and the fixed 2022Q4 exposure and control date.

Dependent Variable: log(**Credit Limit**)

	RegionalExposure		LowTier1Exposure	
	(1)	(2)	(3)	(4)
$t = -4$	−0.500	−0.454	−0.395	−0.389
	(0.377)	(0.382)	(0.363)	(0.351)
$t = -3$	−0.342	−0.405*	−0.356	−0.368
	(0.244)	(0.240)	(0.238)	(0.241)
$t = -2$	−0.186	−0.182	−0.266	−0.245
	(0.180)	(0.184)	(0.195)	(0.196)
$t = -1$	0.079	0.058	0.015	0.021
	(0.052)	(0.039)	(0.041)	(0.040)
$t = +1$	−0.076	−0.126	−0.107	−0.109
	(0.079)	(0.097)	(0.065)	(0.071)
$t = +2$	−0.104	−0.151	−0.118	−0.117
	(0.095)	(0.112)	(0.079)	(0.086)
$t = +3$	−0.052	−0.115	−0.020	−0.026
	(0.125)	(0.139)	(0.114)	(0.116)
$t = +4$	0.078	0.043	0.102	0.112
	(0.155)	(0.162)	(0.135)	(0.126)
BDC FEs	Y	Y	Y	Y
Year-quarter FEs	Y	Y	Y	Y
Horizon-Interacted Controls	N	Y	N	Y
N	764	764	764	764
Within R^2	0.016	0.062	0.012	0.060

Table IA.3. BDC Specialization in Extending Commitments

This table measures BDCs' specialization in unfunded commitments relative to the cross-BDC aggregate commitment book, following Blickle, Parlatore, and Saunders (2025). The specialization measure is the *excess share*: how much a BDC's weight in a given industry, state, or sponsor exceeds the cross-BDC aggregate weight in the same dimension. Top-1 picks the BDC's most overweighted bucket within the BDC-quarter; Top-3 sums the weights of the three largest overweighted buckets. The sample consists of 3,235 BDC-quarters with data on both the commitment book and portfolio holdings. For each BDC-quarter and each industry-group, HQ-state, or sponsor bucket, the excess share is the BDC's own weight in the bucket minus the aggregate weight across BDCs in the same bucket and quarter. Sponsor assignment follows Table 4; sponsor weights are normalized within identified exposure. All rows use the same BDC-quarters with identified sponsor exposure in both books. Each row reports the cross-sectional distribution of the measure, separately for commitment book weights (columns 1–4) and loan portfolio weights (columns 5–8). The Diff column reports the average within-BDC-quarter difference between the commitment book and loan portfolio values, with significance from a paired t-test, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Industry Excess Share

	Commitment Book				Loan Portfolio				Diff
	Mean	P25	Median	P75	Mean	P25	Median	P75	Paired t
Top-1	0.300	0.159	0.245	0.383	0.157	0.080	0.124	0.200	0.142***
Top-3	0.472	0.316	0.444	0.609	0.282	0.169	0.251	0.358	0.190***
N					3,235				

Panel B: HQ State Excess Share

	Commitment Book				Loan Portfolio				Diff
	Mean	P25	Median	P75	Mean	P25	Median	P75	Paired t
Top-1	0.277	0.119	0.217	0.364	0.105	0.052	0.077	0.120	0.172***
Top-3	0.455	0.259	0.416	0.621	0.215	0.124	0.173	0.255	0.240***
N					3,235				

Panel C: Sponsor Excess Share

	Commitment Book				Loan Portfolio				Diff
	Mean	P25	Median	P75	Mean	P25	Median	P75	Paired t
Top-1	0.351	0.133	0.266	0.494	0.125	0.060	0.090	0.149	0.226***
Top-3	0.582	0.315	0.553	0.880	0.262	0.147	0.210	0.320	0.320***
N					3,235				

Table IA.4. Selection of Portfolio Borrowers into Commitment Books

This table reports linear probability regressions of whether a BDC's portfolio company carries an unfunded commitment on borrower characteristics and BDC-borrower relationship characteristics. The sample consists of BDC-borrower-quarter observations for borrowers in BDC portfolio holdings between 2005Q1 and 2025Q4. In column 1, the dependent variable is an indicator for whether the BDC extends any unfunded commitment to the borrower in the quarter. In columns 2 and 3, the sample restricts to BDC-quarters that report the type of commitments, and the dependent variables are indicators for whether the BDC extends a revolver-type or DDTL-type commitment, respectively. The regressors include borrower-level or borrower-quarter variables: Credit Quality, Sponsor Backed, M&A Deal, log(Employees), and log(Age); and BDC-borrower-quarter relationship variables: Dual Held and log(Principal). Credit Quality, Dual Held, and log(Principal) are measured at $t-1$; M&A Deal equals one if the borrower has an M&A deal during quarters $t-1$ through $t-4$. All specifications include industry-year-quarter, HQ state-year-quarter, and BDC-year-quarter fixed effects. Standard errors are two-way clustered at the BDC and borrower levels, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: 1{Commitment Extended}

	Any Commitment (1)	Revolver (2)	DDTL (3)
Credit Quality	0.300***	0.176***	0.073***
	(0.037)	(0.031)	(0.020)
Sponsor Backed	0.046***	0.034***	0.009
	(0.013)	(0.011)	(0.006)
M&A Deal	0.055***	0.026***	0.037***
	(0.007)	(0.006)	(0.007)
Dual Held	0.025**	0.032***	0.000
	(0.013)	(0.012)	(0.006)
log(Employees)	−0.026***	−0.017***	−0.008***
	(0.003)	(0.003)	(0.002)
log(Age)	−0.017***	−0.004	−0.009***
	(0.004)	(0.004)	(0.003)
log(Principal)	0.030***	0.024***	0.010*
	(0.007)	(0.005)	(0.005)
Industry-Year-Quarter FEs	Y	Y	Y
HQ State-Year-Quarter FEs	Y	Y	Y
BDC-Year-Quarter FEs	Y	Y	Y
N	301,817	270,588	270,588
R^2	0.377	0.413	0.265

Table IA.5. Lender Types of BDCs' Credit Lines

This table summarizes the lenders that provide credit lines to BDCs between 2005Q1 and 2025Q4. Lender names are extracted from 10-K and 10-Q credit-agreement disclosures and assigned into four lender types: US bank, Foreign bank (foreign-headquartered banks operating in the US through a New York or London branch, identified by parent-bank home jurisdiction such as Deutsche Bank AG, BNP Paribas, Sumitomo Mitsui, or UBS), Nonbank (independent nonbank lenders, asset managers, and insurance companies), and Other (BDC investment adviser affiliates, trust companies, and central bank discount-window borrowings). SEC-registered broker-dealers are reclassified into the type of their parent. Panel A reports the count of distinct lender entities by type, total lender appearances (one observation per BDC-facility-quarter-lender combination), and admin-agent-only appearances. Panel B lists the top 15 administrative agents ranked by facility-quarters served as admin agent, with their type, the number of distinct BDC borrowers (# BDC), the number of distinct credit-line agreements (# CLID), and total quarterly observations.

Panel A: Composition by lender type

Lender type	# Lenders	Total Obs	Admin Obs
US bank	97	7,243	4,811
Foreign bank	26	2,358	2,065
Nonbank	33	1,135	866
Other	15	262	220
Total	171	10,998	7,962

Panel B: Top 15 administrative agents (by facility-quarters served as admin agent)

Lender (canonical name)	Type	# BDC	# CLID	Total Obs
JPMorgan Chase Bank, N.A.	US bank	47	74	895
Deutsche Bank AG, New York Branch	Foreign bank	29	47	558
ING Capital LLC	Nonbank	23	26	518
Citibank, N.A.	US bank	26	36	480
Sumitomo Mitsui Banking Corporation	Foreign bank	31	44	435
Wells Fargo Bank, N.A.	US bank	30	36	418
Wells Fargo Securities, LLC	US bank	13	21	300
SunTrust Bank	US bank	9	12	265
BNP Paribas	Foreign bank	19	26	256
Bank of America, N.A.	US bank	21	31	247
KeyBank, N.A.	US bank	10	17	236
Natixis, New York Branch	Foreign bank	15	21	222
Goldman Sachs Bank USA	US bank	16	17	218
Truist Bank	US bank	15	18	200
Capital One, N.A.	US bank	12	14	176

Table IA.6. Events of BDCs' Bank Credit Lines

This table summarizes contractual events on BDCs' bank credit lines between 2005Q1 and 2025Q4, identified from 10-K and 10-Q narratives. Each event records a discrete change to one credit-line agreement: inception of a new facility, amendment of an existing facility, exercise of an accordion option, termination, or replacement; multi-field amendments are split into one row per field changed. The sample contains 6,584 events across 196 BDC CIKs and 680 distinct credit-line IDs (CLIDs). Panel A reports the composition of all events by event type. Panel B reports amendment events by the contractual term modified, alongside the share of those amendments that move the term up versus down (direction is not applicable for categorical fields such as benchmark, lender syndicate, subsidiary borrower, covenants, and facility name).

Panel A: Events by type

Category	Count	Share (%)
Inception (new credit line)	2,224	33.8
Amendment (term change)	3,729	56.6
Accordion exercise (commitment increase via accordion)	327	5.0
Termination (facility ended)	205	3.1
Replacement (facility refinanced into new agreement)	99	1.5
Total events	6,584	100.0

Panel B: Amendments by field changed (with directional split)

Field changed	Count	Share (%)	% increase	% decrease
Credit-limit (commitment size)	1,294	34.7	71.3	28.1
Spread over benchmark	707	19.0	30.6	61.3
Maturity date	795	21.3	99.1	0.9
Revolving (reinvestment) period	335	9.0	99.7	0.3
Accordion cap (max upsize)	164	4.4	92.1	7.1
Benchmark rate (e.g., LIBOR-to-SOFR)	157	4.2	–	–
Lender syndicate composition	101	2.7	–	–
Subsidiary / SPV borrower	27	0.7	–	–
Covenants	134	3.6	–	–
Facility name / parties	15	0.4	–	–
Total amendment-field changes	3,729	100.0		

Table IA.7. Accordion Feature in BDCs' Bank Credit Lines

This table summarizes the prevalence and use of accordion features in BDCs' bank credit lines between 2005Q1 and 2025Q4. An accordion feature gives the borrower the right to upsize the facility (above the existing credit limit) without negotiating a new agreement, subject to a contractually specified accordion cap. A credit line is classified as having an accordion feature if its disclosure history contains an explicit accordion exercise event, an amendment to the accordion cap, or a mention of an accordion option in the inception text. The sample is 680 distinct credit lines (CLIDs) across 198 BDCs. Panel A reports prevalence and exercise activity at the CLID level. Panel B reports the distribution of the accordion cap to credit limit multiplier across the 137 CLIDs with accordion feature for which both values are extracted with consistent units.

Panel A: Prevalence and exercise activity

	Count	Share (%)
Total credit lines (CLIDs)	680	100.0
CLIDs with accordion feature ever	206	30.3
of which: exercised accordion at least once	108	52.4*
Total accordion exercises in sample	327	
mean / median / max exercises per active accordion	3.03 / 2 / 16	

Panel B: Accordion cap / credit limit multiplier

	Mean	SD	Min	P10	P25	P50	P75	Max
Multiplier (N = 137 CLIDs)	1.42	0.70	0.68	1.00	1.00	1.14	1.56	4.80

Table IA.8. Illustrative Case: Ares Capital's Commitment Book and Bank Credit Lines Around the 2020Q1 COVID Stress

This table illustrates the unfunded commitment book and bank credit lines of Ares Capital around the 2020Q1 COVID stress. Panel A lists the eight largest declines in unfunded commitments among continuing borrowers between 2019Q4 and 2020Q1. Panel B reconciles the book-wide change in unfunded commitments over the same quarter: continuing borrowers account for a total decline of $593.6 million, while facilities ending at zero and borrowers leaving the book reflect position endings rather than borrower draws. Panel C lists Ares's own bank credit lines from our as-borrower credit-line panel—the administrative agent, committed credit limit (as of 2020Q1), and drawn balances—showing the liability-side response to the drawdown wave. All amounts in USD million.

Panel A: Top 8 Continuing-Borrower Unfunded Declines, 2019Q4–2020Q1

Borrower	Unfunded 2019Q4	Unfunded 2020Q1	Δ Unfunded
Foundation Risk Partners	69.6	6.4	−63.2
Premise Health	38.4	4.0	−34.4
Thrive Pet Healthcare	36.3	4.8	−31.5
ENTRUST Solutions Group	30.6	5.3	−25.3
The Hilb Group	31.6	8.3	−23.3
Mavis Tire Supply	34.6	11.3	−23.3
Belfor USA Group	22.5	0.2	−22.3
Paciolan	21.7	0.5	−21.2

Panel B: Book-Wide Reconciliation, 2019Q4–2020Q1

Continuing borrowers (118): total change	−593.6
Facilities ending at zero (46): endings, not draws	−237.9
Borrowers leaving the book (12): endings, not draws	51.3

Panel C: Ares's Bank Credit Lines, 2019Q4–2020Q1

Facility	Credit Limit	Drawn 2019Q4	Drawn 2020Q1	Δ Drawn
Syndicated revolving facility (JPMorgan)	3,605	2,250	2,265	+15
Funding facility (Wells Fargo)	1,275	638	913	+275
Funding facility (SMBC)	725	301	475	+174
Total	5,605	3,189	3,653	+464

Table IA.9. Summary Statistics for Liquidity-Response Regressions

This table reports summary statistics for the variables used in Table IA.10 and Table IA.11. Variables scaled by assets are divided by lagged total assets. All controls in Panel C are measured in the preceding quarter. All scaled variables are winsorized at the 1st and 99th percentiles within the pre-FE common sample, matching the regression specifications.

Variable	*N*	Mean	SD	P25	Median	P75
Panel A. Investment demand and bank credit line response						
Inv. cash outflow / TA	3,735	0.197	0.215	0.067	0.127	0.237
Bank credit line drawdown / TA	3,735	0.024	0.097	-0.010	0.000	0.046
Bank credit line amendment / TA	3,735	0.014	0.060	0.000	0.000	0.000
Bank credit line inception / TA	3,735	0.033	0.125	0.000	0.000	0.000
Bank credit line termination / TA	3,735	0.014	0.065	0.000	0.000	0.000
Panel B. Other funding sources						
Inv. proceeds / TA	3,735	0.087	0.123	0.034	0.068	0.112
Equity issue / TA	3,735	0.054	0.133	0.000	0.001	0.062
Dist. cut / TA	3,735	0.013	0.016	0.007	0.012	0.016
Cash use / TA	3,735	-0.002	0.061	-0.015	-0.001	0.013
Panel C. Controls						
Undrawn bank credit line / TA	3,735	0.196	0.208	0.055	0.152	0.267
Debt / TA	3,735	0.379	0.168	0.310	0.419	0.492
Cash / TA	3,735	0.060	0.082	0.014	0.029	0.067
log(TA)	3,735	6.578	1.387	5.749	6.592	7.506

Table IA.10. BDC Liquidity Needs and Bank Credit Lines

This table decomposes the BDC's quarterly bank credit line response to investment cash demand across four facility-level margins. Every observation in the sample is a BDC-quarter in 2005Q1–2025Q4. The dependent variables are constructed at the bank credit facility level and aggregated to the BDC-quarter level. Column 1 reports the active drawdown on continuing facilities (the change in outstanding); column 2 reports the change in credit limit on continuing facilities (limit amendment); column 3 reports the credit limit of newly originated facilities (inception); column 4 reports the credit limit of facilities that close (termination, signed positive as a capacity loss). All four outcomes are scaled by lagged total assets. The regressor is the BDC's gross investment cash outflow scaled by lagged total assets. Lagged controls are undrawn bank credit line capacity, total debt, cash and equivalents, and log assets, all scaled by lagged total assets where relevant. Standard errors are clustered at the BDC level, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Δ Bank Credit Line Capacity / TA

	Drawdown (1)	Amendment (2)	Inception (3)	Termination (4)
Inv. Cash Outflow / TA	0.116***	0.048***	0.065***	−0.013
	(0.017)	(0.009)	(0.024)	(0.010)
Undrawn Bank Credit/TA	0.135***	−0.048***	−0.077***	0.062***
	(0.019)	(0.010)	(0.026)	(0.014)
Debt/TA	−0.120***	0.022*	−0.075**	−0.010
	(0.024)	(0.012)	(0.036)	(0.017)
Cash/TA	0.013	0.004	0.013	−0.002
	(0.030)	(0.021)	(0.048)	(0.019)
log(TA)	−0.003	−0.007***	−0.036***	−0.005
	(0.005)	(0.003)	(0.008)	(0.004)
BDC FEs	Y	Y	Y	Y
Year-quarter FEs	Y	Y	Y	Y
N	3,735	3,735	3,735	3,735
R^2	0.300	0.194	0.225	0.239

Table IA.11. BDC Investment Cash Needs and Other Sources of Liquidity

This table decomposes BDC investment cash needs across the four funding sources, regressing each source on the same investment-demand regressor and controls. The sample is the same BDC-quarters in 2005Q1–2025Q4 as Table IA.10. Each column reports a separate regression for one funding source, signed so positive values are increases in cash: investment proceeds from sales and principal repayments, equity issuance, distribution cuts, and balance-sheet cash use. All four sources are scaled by lagged total assets. The regressor is the BDC's gross investment cash outflow scaled by lagged total assets. Lagged controls are undrawn bank credit line capacity, total debt, cash and equivalents, and log assets, all scaled by lagged total assets where relevant. Standard errors are clustered at the BDC level, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Funding Amount / TA

	Inv. Proceeds (1)	Equity Issue (2)	Dist. Cut (3)	Cash Use (4)
Inv. Cash Outflow / TA	0.233***	0.266***	0.001	−0.022**
	(0.031)	(0.026)	(0.004)	(0.011)
Undrawn Bank Credit/TA	−0.054***	−0.069***	−0.002	0.037***
	(0.015)	(0.019)	(0.001)	(0.011)
Debt/TA	−0.021	0.123***	−0.017***	−0.008
	(0.026)	(0.034)	(0.004)	(0.019)
Cash/TA	−0.174***	0.017	−0.012***	0.348***
	(0.034)	(0.053)	(0.004)	(0.035)
log(TA)	0.006	−0.077***	−0.001	0.018***
	(0.006)	(0.008)	(0.001)	(0.004)
BDC FEs	Y	Y	Y	Y
Year-quarter FEs	Y	Y	Y	Y
N	3,735	3,735	3,735	3,735
R^2	0.373	0.580	0.305	0.209

Table IA.12. Liquidity Backing for BDCs with Zero Dry Powder

This table repeats the regressions in Panel A of Table 7 for BDC-quarters with zero lagged dry powder. Every observation in the sample is a BDC-quarter with a bank credit line in 2005Q1–2025Q4. Dry powder is uncalled investor capital measured at the preceding financial statement. The dependent variable is the BDC's total undrawn bank credit across its facilities in column 1, and the sum of the BDC's undrawn bank credit and cash holdings in column 2, both scaled by lagged total assets. *Total Unfunded/TA* is the BDC's total unfunded commitments extended to borrowers on its commitment book, scaled by lagged total assets. *Debt/TA* is the BDC's lagged total debt scaled by lagged total assets. log(*TA*) is the natural logarithm of the BDC's lagged total assets. *Listed* is an indicator that equals one if the BDC is exchange-listed in the quarter. Standard errors are clustered at the BDC level. *, **, and *** represent 10%, 5%, and 1% levels of statistical significance. The p-value row tests $H_0 : \beta \geq 1$ against $H_1 : \beta < 1$ for the coefficient on *Total Unfunded/TA*.

	Undrawn Bank Credit	Undrawn Bank Credit + Cash
	(1)	(2)
Total Unfunded / TA	0.391^{**}	0.429^{**}
	(0.155)	(0.177)
Debt / TA	-0.168^{*}	-0.218^{*}
	(0.089)	(0.110)
log(TA)	-0.124^{***}	-0.151^{***}
	(0.018)	(0.022)
Listed	0.085^{***}	0.092^{***}
	(0.031)	(0.026)
BDC FEs	Y	Y
Year-Quarter FEs	Y	Y
R^2	0.567	0.565
N	3,734	3,734
p-value ($H_0 : \beta \geq 1$)	0.000	0.001