# Credit Commitments by Nonbanks*

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**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 pattern in nonbank lending: business development companies (BDCs) extend substantial credit commitments to borrowers, with commitments growing faster than total BDC assets. These off-balance-sheet commitments are concentrated, exposing BDCs to undiversified borrower liquidity shocks—a risk they manage with credit lines provided by banks. We develop a model of layered liquidity insurance along the credit chain: the BDC pools borrower firms to partially diversify idiosyncratic shocks and uses a bank credit line to backstop residual liquidity risk. In equilibrium, the nonbank optimally provides only partial liquidity insurance: its limited bank credit line rations borrower drawdowns when liquidity needs are widespread. We test this prediction empirically and find supportive evidence.

**JEL Classification**: G21, G23, G32

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

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# 1 Introduction

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 pattern in 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 assets by the end of 2025. This pattern suggests that credit commitments provided by nonbanks have become an increasingly important source of liquidity insurance to corporate borrowers.

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

[1] See Block, Jang, Kaplan, and Schulze (2024); Buchak, Matvos, Piskorski, and Seru (2018); He, Huang, and Zhou (2023); Huang (2021).

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

We document two empirical facts. First, BDCs' credit commitments expose them to large and volatile liquidity shocks. We measure the liquidity shock a BDC experiences in a quarter as the change in unfunded commitments (i.e., undrawn credit extended by the BDC) across the borrowers in its commitment book, and its volatility as the time-series standard deviation of this shock. A typical BDC's volatility is about two and a half times as large as that of an equal-weighted benchmark formed as the aggregate of all BDCs' unfunded commitments, and even the least volatile quartile of BDCs is nearly twice as volatile as the benchmark. These shocks are also sizable: a one-standard-deviation quarterly shock could deplete the BDC's cash holdings in about 15% of BDC-quarters, and the magnitude is even more pronounced for BDCs with greater commitment books.

Two economic forces give rise to these large and volatile shocks: book concentration and shock commonality. BDC commitment books are substantially more concentrated by borrower industry, geography, and sponsorship, relative to their on-balance-sheet loan portfolios. This concentration reflects lender information in specific borrower segments, as the commitments also exhibit stronger segment specialization than loan holdings. Within each segment, BDCs further selectively extend commitments to borrowers with better credit quality, sponsor backing, dual debt-and-equity exposure, and recent acquisition activity, suggesting borrower-level risk considerations. Moreover, borrower liquidity shocks also carry a common component, with the 2020Q1 COVID episode as the most visible example. A concentrated book with correlated borrower liquidity shocks leaves the BDC with undiversified exposures.

Second, BDCs manage this liquidity risk through bank credit lines they receive as bor-

rowers. In the cross section, BDCs with larger commitments to borrowers reserve larger undrawn bank credit lines. These undrawn bank credit lines, not cash, provide a liquidity backstop. When cash needs arise, BDCs not only draw cash from their existing bank credit lines but also expand their committed capacity, by either amending credit limits upward or entering into new facilities. This backstop is also resilient to stress: the credit limits to BDCs did not contract when the banks were under pressure, such as during the 2023 regional bank crisis. 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 portfolio firms draw on their direct lenders, who in turn draw on their bank facilities—to our knowledge, we offer the first study to document it in the data.

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? And if so, how does this difference shape the behavior of the borrowers they insure?

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 many nonbank lenders, the bank channels the

spare capacity of BDCs with few portfolio drawdowns to those with many.

To study liquidity provision along the credit chain, we first show that a benchmark of direct bank lending, which pools middle-market firms' shocks completely, delivers full insurance. Because regulatory capital rules disincentivize direct lending, banks instead reach these firms indirectly through the credit chain—a form of regulatory arbitrage. The chain, however, delivers only *partial insurance*, owing to the BDC's bankruptcy cost, which reflects its undiversified commitment book and, as a nonbank, its lack of a public backstop. 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.

We find evidence consistent with BDCs providing only partial liquidity insurance. In levels, a one-dollar increase in unfunded commitments to borrower firms is associated with only about \$0.54 of undrawn bank credit slack, and the slack available to cover drawdowns is smaller still because BDCs also tap these lines for other liquidity needs. Ex post, when draw pressure rises in a borrower's industry, borrowers of liquidity-stressed BDCs draw down significantly less than borrowers of unstressed BDCs facing the same pressure, and the attenuation grows with the severity of the BDC's liquidity stress.

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, 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.[2] 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.[3]

We also speak to the *empirical literature on credit lines* (e.g., Sufi, 2009, Greenwald, Krainer, and Paul, 2025; see Demiroglu and James, 2011 for a review). 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

[2]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.

[3]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).

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 as evidenced by Acharya, Engle, Jager, and Steffen (2024): when the aggregate COVID-19 shock hit, banks that had committed credit lines underperformed in the stock market.

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 (2024) 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, 2024). 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, 2024), 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 and complementary work, Flanagan and Jang (2026) argue that liquidity sources other than bank credit lines, such as uncalled investor capital, also contribute to private credit lenders' provision of credit lines.

# 2 Data

## 2.1 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, predominantly small and middle-market private U.S. operating companies. BDCs invest across the corporate capital structure but concentrate in directly originated 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. Our study focuses on public BDCs, which are subject to public disclosure requirements and file periodic reports with the SEC.[4] These BDCs consist of exchange-listed BDCs, whose equity shares trade on exchanges, and non-traded BDCs, which offer only periodic share repurchases, commonly capped near 5% of net asset value per quarter.

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

[4]We exclude private BDCs, which rely on private market investors and are exempt from these disclosures.

growing parts of the financial system, now with over $1 trillion in the United States.[5] The universe of BDCs we identify from SEC EDGAR comprises 245 unique BDCs that are ever public between 2005Q1 and 2025Q4, with combined total assets of roughly $550 billion as of 2025Q4. These public BDCs offer a transparent window into the opaque private-credit market. Figure IA.4 in the Internet Appendix shows the total number and assets of these listed and non-listed BDCs.

## 2.2 Data Sources

We assemble four datasets covering business development companies (BDCs): (i) a BDC-quarter panel of balance-sheet, cash-flow, and off-balance-sheet commitment items; (ii) the unfunded-commitment book at the BDC-quarter-borrower-facility level, covering the credit commitments BDCs extend to portfolio companies; (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.7 provides details on the collection and processing of these datasets.

*BDC-quarter panel.* We identify the universe of public 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 6,435 BDC-quarters across 245 unique BDCs over 2005Q1–2025Q4 in which the BDC has an active N-54A election and reports the main balance-sheet items. The main BDC-quarter variables are (a) the BDC's total unfunded commitments (the credit committed but not yet funded)

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

to portfolio companies; (b) balance-sheet items including total assets, total debt, total equity, and cash and equivalents; and (c) statement-of-cash-flow items including operating, investing, and financing cash flow subtotals together with gross investment purchases, gross investment sales and repayments, distributions paid, and equity issuance.

*Unfunded credit in commitment books.* For the subsample of BDC-quarters in which the filing's commitments-and-contingencies note discloses a borrower-level breakdown of the unfunded loan commitments, we hand-collect each portfolio company'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.7.6).

*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.9 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 5,769 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 Capital Structure data merged with Compustat quarterly to construct aggregate public-firm drawdown factors, with details in Internet Appendix IA.8.2. We also cross-validate the hand-extracted BDC balance-sheet items against Compustat and CIQ where coverage permits.

## 2.3 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 lenders, 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 dollar change in unfunded amount is −$0.4 million per quarter, and the average percentage change is −2.8%, both consistent with net drawdown on average. Borrowers actively draw down—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.

# 3 Empirical Patterns

We document three empirical patterns in this section. First, BDC credit commitments are an economically important and growing source of corporate liquidity insurance. Second, BDCs' commitment books expose them to volatile borrower liquidity shocks. Finally, 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 4, as well as its key premise that BDCs' liquidity risk from borrowers is undiversified.

## 3.1 Economic Significance of BDCs' Unfunded Commitments

BDC unfunded commitments to portfolio companies are an economically important source of liquidity insurance. Figure 1, Panel A compares the total unfunded commitments BDCs extend to portfolio companies with those banks extend to corporate borrowers (commercial and industrial firms and financial institutions), both scaled by the sector's total assets. The commitment-to-asset ratio of BDCs has been rising over the past decade, and by 2025Q4 the two ratios are comparable at about 15%. Panel B shows the cross-sectional distribution of this ratio as of 2025Q4. Whereas most banks have modest ratios, typically below 10%, about 60% of BDCs have a ratio above 10%, suggesting that liquidity insurance provision is now widespread within the BDC sector. Although this ratio is not fully comparable between BDCs and banks due to differences in asset composition, it shows that BDCs provide an increasingly significant amount of corporate liquidity insurance.

Figure 2 plots, in aggregate, the liquidity BDCs provide to portfolio companies and the liquidity BDCs can themselves access. First, the total amount of BDC unfunded commitments grew rapidly, from near zero in 2005 to roughly $80 billion by 2025. Second, this growth is broad-based: the number of BDCs with unfunded commitments has grown alongside the aggregate. Third, the liquidity BDCs provide is comparable in scale to the liquidity available to them: aggregate undrawn bank credit line capacity grows alongside their unfunded commitments to portfolio companies, and BDC cash holdings provide a smaller additional buffer. This parity between liquidity provided and liquidity available, together with their growing relevance, motivates us to write a credit chain model of two-layered credit line insurance, which we formalize in Section 4.

## 3.2 BDC Exposure to Borrower Liquidity Shocks

In this subsection, we quantify liquidity shocks from BDCs' commitment books and identify two economic forces that drive the BDC-level exposure to those shocks. Throughout, let $u_{i,\ell,t}$ denote BDC $\ell$'s unfunded commitment to borrower $i$ in quarter $t$. Given the nature of the data (see Internet Appendix Section IA.8.1 for details), we proxy for cashflows related to drawdown activity using changes in unfunded commitments of continuing positions that are observed in two consecutive quarters. We use two alternative measures of borrower liquidity shocks: a continuous percentage change $\Delta u_{i,\ell,t}/u_{i,\ell,t-1}$, and a binary indicator $\mathbf{1}\{\Delta u_{i,\ell,t} < 0\}$ for whether the borrower draws cash from the commitment.

### 3.2.1 Quantifying Liquidity Shocks from Commitment Books

BDC commitment books experience large quarterly liquidity shocks, well beyond what a fully diversified book of commitments would experience. To quantify these BDC-level shocks, we restrict the sample of BDC-borrower-quarter observations to BDC-quarters with at least five borrowers and to BDCs with at least 12 qualifying quarters. For each BDC in this sample, we compute the time-series standard deviation of its quarterly liquidity shock. We then compare this BDC-level volatility to a fully diversified benchmark, defined as the volatility of an equal-weighted book of all BDCs' commitments over the same time window.

The average BDC's volatility is 12.2% per quarter on the continuous measure and 13.7% on the binary measure, roughly three times as large compared with 4.0% and 5.1% for the diversified benchmark. In the cross section, the BDC-level volatility is consistently above the benchmark (Internet Appendix Table IA.1 reports the distribution). This volatility gap indicates that borrower liquidity shocks do not fully diversify at the BDC level; instead, BDCs are exposed to volatile liquidity shocks driven by their borrowers' drawdown activity.

Table 3 translates this volatility into dollar magnitudes by multiplying each BDC's time-

series standard deviation of liquidity shock by its lagged total unfunded commitments.[6] The estimated dollar volatility is large: the shock equals 24.5% of the BDC's lagged cash holdings for the median BDC-quarter, and it exceeds the BDC's cash holdings in 15.3% of BDC-quarters. The magnitude is 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.

### 3.2.2 Concentration of Commitment Books

Book concentration is the parimary reason of the large BDC-level volatility. We construct a sample of 3,236 BDC-quarters with data on both commitment books and portfolio holdings and separately compute concentration measures for these off- and on-balance-sheet exposures.[7] At the borrower's industry, headquarters-state, and PE sponsor levels, we use the Herfindahl–Hirschman Index (HHI) and top-three shares as concentration measures. Table 4 shows that BDC commitment books 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 0.13 versus 0.04 at the sponsor level. The same pattern holds when concentration is measured by top-three shares. The differences in average concentration measures are all statistically significant.

Why do BDCs hold such concentrated commitment books? One reason is *specialization*: BDCs may deliberately over-weight 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.

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

[7] 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.

Table 5 shows that at the industry level, the median BDC's largest excess share is 25 pp for commitment 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 (22 pp versus 9 pp for Top-1 and 49 pp versus 20 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.

Beyond specialization, 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 6 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.[8] 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 to the borrower also positively predicts commitment extension. Overall, these

[8]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.

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

### 3.2.3 Commonality of Borrower Liquidity Shocks

A secondary reason of the large BDC-level volatility is commonality in borrower liquidity shocks, which cannot be diversified away even with a perfectly diversified commitment book. Figure 3 plots the quarterly averages of the two borrower liquidity shock measures between 2017Q1–2025Q4. A salient event is the 2020Q1 COVID drawdown, where the average percentage change in unfunded drops to roughly $-25\%$ and the fraction of borrowers actively drawing reaches about 55%. Across commitment types, revolvers show a stronger COVID-quarter co-movement relative to DDTLs (Figure IA.1 in the appendix). These episodes of synchronized drawdown suggest the existence of commonality across borrowers.

Table 7 reports univariate panel regressions of the borrower liquidity shock on time-series factors. 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 lagged Debt/EBITDA buckets representing different credit profiles, with details in Internet Appendix IA.8.2. The estimates suggest that BDC borrowers' liquidity shocks comove with the drawdowns of public firms, especially public firms with higher leverage or negative earnings. Panel B regresses the shock on market-wide macro and credit-cycle 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.

These panel regressions illustrate which factors the liquidity shocks co-move with. To quantify the undiversified component of these shocks, we present a variance decomposition in Table 8 via different sets of fixed effects. 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, indicating that the shocks are correlated across borrowers within the same industry and geography. Combined with the book concentration documented in Section 3.2.2, these comovements give rise to the sizable BDC-level exposure to volatile liquidity shocks. Indeed, BDC-by-time fixed effects absorb 7–9%, suggesting that a substantial share of the shocks fail to diversify away within the BDC's commitment book. This undiversified liquidity risk is the empirical counterpart of the key assumption in our model (Section 4): because a BDC pools only a finite, concentrated book of borrowers with correlated shocks, substantial liquidity risk remains at the BDC level. The next subsection shows that bank credit lines serve as a backstop for this residual risk, which the model casts as the second layer of insurance in the credit chain. In the model, because shocks in tail states can still threaten the BDC's own survival, we show that the BDC may optimally provide only partial liquidity insurance.

## 3.3 Bank Credit Lines as a Liquidity Backstop

When borrowers draw their unfunded commitments, the BDC has to deliver cash, so the volatility documented in Section 3.2 gives rise to liquidity risk for BDCs. This subsection examines how BDCs satisfy these drawdown requests and manage the liquidity risk with bank credit lines.

Figure 2 has shown that BDCs' aggregate unfunded commitments to borrowers and their aggregate undrawn credit lines from banks have been growing together over 2005–2025 at a similar scale. 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 in a range of roughly 40–50% over time, which provides a liquidity backstop for managing the liquidity shocks from the commitment books and other cash needs. Indeed, BDCs themselves

identify bank credit lines as the primary backstop for their unfunded commitments in regulatory filings.[9] 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.[10] Moreover, because BDCs must distribute most of their income to maintain tax status, they hold only a small cash buffer.[11] So bank credit lines, rather than cash, are likely the most important liquidity backstop in terms of economic magnitude.

The backstop also operates actively in flows. In the Internet Appendix (Section IA.10 and Table IA.3), we show 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.5 shows no contraction in committed bank credit limits for BDCs more exposed to regional or low-capital banks around the 2023 regional bank crisis. Taken together, the evidence indicates that BDCs use bank credit lines as an important backstop for providing liquidity to their own borrowers.

[9] 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.2 reports disclosure status over the full sample.

[10] Non-traded BDCs may hold uncalled capital commitments from limited partners (LPs), but such commitments are a funding source that itself requires 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).

[11] Internet Appendix Figure IA.3 shows that the ratio of BDCs' undrawn bank credit and cash holdings is several times that of both nonfinancial and financial public firms.

# 4 A Model of Layered Credit Line Provisions

We develop a model of an intermediation chain in which a bank extends a credit line to a BDC, which in turn provides credit commitments to borrower firms. The model features two layers of insurance: the BDC pools its portfolio firms but, given its concentrated commitment book, diversifies their idiosyncratic liquidity shocks only partially; the bank, with its large balance sheet, insures the BDC against the residual liquidity risk.

We show that partial insurance arises in the credit chain: because BDC insolvency entails a deadweight loss, states with widespread firm drawdowns are socially costly to insure.

## 4.1 Environment and Agents

There are three dates, $t = 0$, $t = 1$ and $t = 2$, and there is no discounting. For simplicity, interest rates do not compound: a dollar advanced at either $t = 0$ or $t = 1$ owes the same rate at $t = 2$. The economy is populated by a continuum of firms with total measure $n$, a unit continuum of BDCs, and a single bank. In the baseline model, all agents are risk-neutral.

**Firms.** Firms are ex ante identical. At $t = 0$, each firm needs to finance 1 dollar to launch a long-term project that, if continued to maturity, produces $y > 1$ at $t = 2$. At the interim date $t = 1$, with probability $p$ the firm is hit with a liquidity shock of size $\rho > 0$: it must raise this additional amount to continue, and absent the injection the project is liquidated and yields zero. In the baseline model, liquidity shocks are purely idiosyncratic and independent across firms; Section 4.4.2 introduces an aggregate component. We also treat $p$ as fixed until Section 4.4.1, where firms can influence their own exposure through costly liquidity management. Liquidity shocks are verifiable, so a firm cannot pretend to be shocked and divert funds when credit is available.

A portion $\Delta$ of the firm's output $y$ is nonpledgeable. One microfoundation is moral

hazard, under which $\Delta$ is the rent the entrepreneur must retain to be induced to exert effort.[12] Let $R > 1$ denote the gross risk-free rate, the opportunity cost of outside funds. We maintain the following parameter assumption.

**Assumption 1.**

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

The second inequality states that continuing a shocked firm is socially valuable: its output exceeds the cost of the required liquidity injection. Yet a shocked firm cannot raise $\rho$ in the spot market at $t = 1$: by the first inequality, its pledgeable income $y - \Delta$ falls short of the required repayment $R\rho$, even for fully senior claims that dilute existing $t = 0$ creditors. Liquidity must therefore be arranged in advance.

Credit lines are the classic form of liquidity insurance offered by intermediaries (Holmström and Tirole, 1998): an intermediary commits to provide liquidity to a firm up to a prespecified limit, which the firm draws on when shocked. The insurance is enabled by pooling firms ex ante, before shocks realize; ex post, firms without liquidity shocks do not draw, and their spare liquidity goes to shocked firms. The spot market, by contrast, lacks such commitment and responds to realized shocks as discussed above. Because liquidity shocks are purely idiosyncratic, they are fully diversified when pooled across sufficiently many firms—in the model, on the bank's balance sheet. The BDC's commitment book, however, is concentrated (Section 3.2) and leaves the BDC with residual liquidity risk. In this paper, we study how BDCs provide such liquidity insurance.

The insurance logic also explains why saving cash against the shock is inefficient. Holding cash is costly, and with probability $1-p$ the shock does not hit and the precautionary buffer

[12] Formally: After the liquidity shock is realized, the entrepreneur chooses whether to exert effort. If effort is exerted, the project succeeds for sure at $t = 2$; if the entrepreneur shirks, it succeeds only with probability $\pi < 1$ and the entrepreneur enjoys a private benefit $B$. Assume that it is socially beneficial to implement effort, so the entrepreneur must retain at least $\Delta \equiv \frac{B}{1-\pi}$, leaving only $y - \Delta$ pledgeable to outside creditors.

sits idle—a waste that credit lines avoid by pooling across firms. To focus on credit lines, we impose the following condition, under which cash saving is not viable:

$$y - \Delta + (1-p)\rho \leq (1+\rho)R. \tag{2}$$

The firm must raise $1+\rho$ at $t=0$ to fund the project and the cash buffer, but its pledgeable income $y-\Delta$ plus the expected unused buffer $(1-p)\rho$ falls short of the required repayment $(1+\rho)R$.

Firms may seek financing either directly from the bank or from the BDC. We briefly analyze direct bank lending as a benchmark (Section 4.2). Our focus is the credit chain, in which firms obtain funding and liquidity insurance from BDCs, and BDCs in turn from the bank.

Throughout, we focus on debt instruments to match empirical facts. An entity that defaults incurs a binary social deadweight loss; for a firm, this loss is $\lambda > 0$. Firm defaults coincide with liquidity shocks: a funded shocked firm owes at least $R(1+\rho)$ but can pledge only $y-\Delta < R\rho$ (Assumption 1); an unfunded shocked firm is liquidated and repays nothing; an unshocked firm repays in full. The expected firm-level bankruptcy loss is therefore $np\lambda$, independent of the financing arrangement and of liquidity coverage.

**BDC.** A continuum of business development companies (BDCs), indexed by $j \in [0,1]$, operate in distinct segmented markets; we focus on a representative BDC and omit the index $j$ when no confusion arises.

Motivated by the evidence in Section 3.2, we model a BDC's portfolio as a *finite* set of $n$ firms (of measure $ndj$ for BDC $j$). To isolate the trade-offs in liquidity provision in the credit chain, we first abstract away from the financial instruments between the BDC and its portfolio firms and treat them as a single bundle. We solve for the allocation that

maximizes their surplus subject to market frictions, and later verify that this allocation can be implemented via the BDC providing term loans and credit lines to portfolio firms at $t = 0$. Because firm defaults coincide with liquidity shocks and are invariant across the debt instruments we consider (as discussed above), we include the expected bankruptcy loss $np\lambda$ in the bundle's surplus.

Given the finite portfolio, the cross-sectional distribution of the firms' shocks determines the BDC's liquidity needs. Let $k$ denote the number of shocked firms at a given BDC; then

$$k \sim \text{Binomial}(n, p). \tag{3}$$

In the credit chain we focus on, the BDC manages this liquidity risk with a committed credit line from the bank; the bank provides this insurance by pooling liquidity across all BDCs.

Specifically, at $t = 0$, the BDC obtains a term loan of size $n$ plus a credit line of capacity $m\rho$ from the bank, where $m \in \{0, \ldots, n\}$; the bank charges a capacity-invariant gross rate $R_I$ ($I$ for *i*ntermediary) on any credit extended, and a fee $f(m)$ that adjusts with capacity $m$, both due at $t = 2$. In a state where $k$ portfolio firms are hit by liquidity shocks at $t = 1$, the BDC draws

$$\rho \min\{k, m\}$$

from the bank credit line. When $k > m$, the BDC lacks liquidity to fund all shocked portfolio firms: it draws the full capacity $m\rho$ and randomly funds $m$ of the $k$ shocked firms. This fair lottery arrangement (as in Bernanke and Gertler, 1989) minimizes deadweight loss from liquidation; under the linear setting, it is payoff-equivalent to pro-rata rationing if firm projects could be partially liquidated and each firm received $\frac{m\rho}{k}$ (as in Acharya, Almeida, and Campello, 2013). Therefore, if $m < n$, liquidity shocks are only partially insured in the credit chain: liquidity provision is rationed upon widespread portfolio shocks through the

limited capacity of bank credit line.

In state $k$, the BDC draws $\rho \min\{m, k\}$ from its bank credit line to fund portfolio firms' liquidity shocks. Since $R_I$ accrues on the term loan and on drawn credit, the BDC owes the bank a face value of $R_I [n + \rho \min\{m, k\}]$ at $t = 2$. A total of $n - k + \min\{m, k\}$ projects continue, each generating pledgeable income $y - \Delta$, while unfunded shocked firms are liquidated. The BDC's net worth before any insolvency cost is

$$\Pi_k(m, R_I) = (y - \Delta) [n - k + \min\{m, k\}] - R_I [n + \rho \min\{m, k\}] . \tag{4}$$

The BDC is insolvent when $\Pi_k < 0$. As liquidity shocks are negative NPV to fund ex post, $\Pi_k$ is strictly decreasing in $k$ and the BDC is insolvent exactly when $k$ exceeds the threshold $\hat{k}$ solving $\Pi_{\hat{k}}(m, R_I) = 0$. BDC insolvency entails the binary deadweight loss $n\lambda$ reflecting portfolio size $n$.

The BDC's insolvency cost—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. Essentially, the difference lies in the order of diversification and default assessment: under direct lending, borrower risk is first diversified on the bank's balance sheet; in the credit chain, BDC default is assessed first, before residual risk is pooled upstream by the bank (Jensen's inequality).

Collecting these pieces, the expected social surplus of the BDC and portfolio firms is

$$W^N(m) = \mathbb{E}[y (n - k + \min\{k, m\}) - R (n + \rho \min\{k, m\})] - np\lambda - n\lambda \Pr(\Pi_k(m, R_I) < 0) , \tag{5}$$

where each continued project yields social benefit $y$, and the social costs are the required return $R$ on outside funds, the unavoidable firm-default losses, and the additional loss from BDC insolvency. We solve for the optimal allocation along the credit chain by maximizing

this surplus over $m$, subject to the bank's participation constraint, which we derive next.

**Bank.** Bank lending is subject to regulatory capital requirements, and the risk-weighted capital charge when lending directly to middle-market firms is higher than when lending indirectly through BDCs (Chernenko, Ialenti, and Scharfstein, 2025). We take regulatory costs as exogenous: the per-dollar cost of funding a firm directly is $R + e\kappa_B$, where $e$ is the excess cost of equity and $\kappa_B$ is the risk-based capital charge; for simplicity, we normalize the regulatory cost of funding a BDC to zero, so that its funding cost is simply $R$. In practice, the lower cost of lending to nonbank financial institutions (NBFIs) reflects their lower predicted default risk, driven by diversification and their equity buffers.

The bank operates in a competitive market and breaks even, which pins down the terms of each lending contract. In the case of direct lending, the contract with a firm consists of a term loan of size 1 at $t = 0$ and, if liquidity insurance is provided, a credit line of size $\rho$, both at a gross rate $R_B$ ($B$ for *b*ank) per dollar advanced. For a firm covered by the credit line, break-even requires

$$(1 - p)R_B + p(y - \Delta) = (1 + p\rho)(R + e\kappa_B). \tag{6}$$

Each firm repays $R_B$ if unshocked (probability $1 - p$); if shocked, it defaults under (1) and repays its pledgeable income $y - \Delta$. The bank's expected collections cover the cost of the $1 + p\rho$ dollars it expects to advance. We postpone the coverage choice to Section 4.2, where the break-even condition pools across covered and uncovered firms.

In the case of the credit chain, the bank lends to a continuum of BDCs, and the remaining liquidity shocks at the BDC level follow the binomial distribution of $k$ in (3). From a BDC

and its portfolio firms (treated as a bundle) in state $k$, the bank collects

$$\min\left\{R_I\left[n+\rho\min\{m,k\}\right],\ (y-\Delta)\left[n-k+\min\{m,k\}\right]\right\}. \tag{7}$$

The face value is owed on the term loan $n$ plus the drawn credit $\rho\min\{m,k\}$; in the event of default, the bank recovers the pledgeable income of the $n-k+\min\{m,k\}$ continuing projects. The bank pools all BDCs' residual liquidity shocks, thus providing the second layer of liquidity insurance. Its participation constraint is then

$$f(m)+\mathbb{E}\left\{\min\left\{R_I[n+\rho\min\{k,m\}],(y-\Delta)[n-k+\min\{k,m\}]\right\}\right\}=R[n+\rho\mathbb{E}[\min\{k,m\}]], \tag{8}$$

which pins down the fee $f(m)$ for each credit line capacity $m$.

## 4.2 Direct Bank Lending

We begin with a benchmark in which the bank lends directly to the full measure $n$ of firms. The bank extends a term loan of size 1 to every firm and a credit line of size $\rho$ to a fraction $s\in[0,1]$ of firms. Pooling the mass $sn$ of covered firms fully diversifies their liquidity shocks: exactly a fraction $p$ is shocked, and the total drawdown $snp\rho$ is deterministic.

We solve for the allocation that maximizes social surplus within the class of bank debt specified above, subject to the bank's participation constraint that it breaks even.

$$\begin{aligned} W^B(\kappa_B) \ \equiv\ \max_{s\in[0,1],\ R_B\le y-\Delta}\ & n\left[(1-p+ps)y-(R+e\kappa_B)\left(1+ps\rho\right)\right]-np\lambda \\ \text{s.t.}\quad & (1-p)R_B+ps(y-\Delta)\ =\ (R+e\kappa_B)\left(1+ps\rho\right). \end{aligned} \tag{9}$$

A fraction $1-p+ps$ of projects continues, each producing $y$, while the credit extended is $1+ps\rho$ per firm at social cost $R+e\kappa_B$. The additional term $np\lambda$ is the expected cost of

the borrower defaults caused by the liquidity shocks and is independent of coverage. In the bank's participation constraint, an unshocked firm repays in full at $R_B$, whereas a covered shocked firm defaults under Assumption 1 and repays $y-\Delta$. The bank's total revenue covers its lending cost in the competitive market.

Provided the regulatory cost leaves coverage socially valuable ($y > (R + e\kappa_B)\rho$), social surplus rises with $s$, so full insurance ($s = 1$) is the constrained-efficient allocation, exhausting the diversification benefit of pooling idiosyncratic shocks. This allocation is attainable if the bank's participation constraint can be satisfied: $y-\Delta \geq (R+e\kappa_B)(1+p\rho)$. We introduce the following assumption to ensure that the condition holds absent the regulatory cost ($\kappa_B = 0$):

**Assumption 2.**

$$y - \Delta \;>\; R(1 + p\rho). \tag{10}$$

Under Assumption 2, direct bank lending achieves the first best when $\kappa_B = 0$. Because bank lending to BDCs carries no regulatory cost, the same assumption also ensures—as we show below—that the bank's participation constraint does not restrict liquidity provision in the credit chain.

As the regulatory cost rises, total surplus falls, and the break-even rate $R_B$ rises toward the pledgeability cap $y - \Delta$; eventually full insurance becomes infeasible and coverage is limited by the bank's break-even condition. In the economically relevant region $y > (R + e\kappa_B)\rho$, the solution is:

$$s^*(\kappa_B) = \min\left\{1,\ \bar{s}(\kappa_B)\right\}, \qquad W^B(\kappa_B) = n\left[(1 - p + ps^*)\, y - (R + e\kappa_B)\,(1 + ps^*\rho) - p\lambda\right], \tag{11}$$

where $\bar{s}(\kappa_B)$ is the largest coverage satisfying the participation constraint at $R_B = y - \Delta$, which declines in $\kappa_B$ (Appendix A.1 derives the closed form). The resulting welfare is decreasing in $\kappa_B$.

In sum, direct bank lending delivers full insurance when regulatory costs are low. As regulatory costs rise, direct-lending surplus falls, and the credit chain arises as regulatory arbitrage.

## 4.3 Credit Chain

We now characterize liquidity provision through the credit chain. We first show that partial insurance arises from the BDC's insolvency cost, then compare the chain with direct lending, and finally verify that the optimal allocation is implemented by the contracts observed in practice: term loans and credit lines between banks, BDCs, and individual firms.

### 4.3.1 Liquidity Provision

As credit chain avoids regulatory costs, one might think that adding a middle layer of BDCs in between banks and firms should maintain the full insurance outcome in frictionless direct bank lending. In this part, we show that partial insurance arises in the credit chain due to the insolvency frictions of the BDC. Essentially, due to these costs, states with widespread portfolio shocks are negative NPV to provide insurance.

Given bank term loans plus credit lines, the optimal allocation chooses the bank credit line capacity $m$ that maximize the chain surplus in (5) subject to the bank PC in (8):

$$\begin{aligned} \max_{m\in\{0,\ldots,n\}} \ & \mathbb{E}[y\left(n-k+\min\{k,m\}\right)-R\left(n+\rho\min\{k,m\}\right)]-np\lambda-n\lambda\Pr(\Pi_k(m,R_I)<0) \\ \text{s.t.} \quad & \mathbb{E}\left[\min\left\{R_I\left[n+\rho\min\{k,m\}\right],\ (y-\Delta)\left[n-k+\min\{k,m\}\right]\right\}\right] \\ & \qquad + f(m) = \ R\left[n+\rho\,\mathbb{E}\left[\min\{k,m\}\right]\right], \qquad \text{(Bank PC)} \end{aligned} \tag{12}$$

where the firm-level bankruptcy loss is $np\lambda$ and the BDC-level loss $n\lambda$ incurs with probability $\Pr(\Pi_k < 0)$, with $\Pi_k$ given in (4). One can show that under Assumption 2, full coverage

$m = n$ is feasible.

We add the following assumption, under which the choice of $m$ affects the BDC's default probability; otherwise, the insolvency loss is constant across capacities and the capacity choice is degenerate.

**Assumption 3.** *The contractual bank rate and portfolio size satisfy*

$$R_I < y - \Delta < R_I \rho, \qquad \left\lfloor \frac{n[(y-\Delta) - R_I]}{y - \Delta} \right\rfloor > \left\lfloor \frac{n[(y-\Delta) - R_I]}{R_I \rho} \right\rfloor. \tag{13}$$

Even with a committed bank credit line, 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 limits this exposure by choosing a smaller line as we show in Proposition 1.

**Proposition 1.** *Under Assumptions 1–3, there exists a cutoff $\hat{\lambda} > 0$ such that $\lambda < \hat{\lambda}$ implies $m^* = n$, while $\lambda > \hat{\lambda}$ implies $m^* < n$. For sufficiently large $\lambda$, the unique optimum is the largest capacity attaining the minimum BDC default probability.*

Covering a shocked firm is costly ex post: the draw advances $\rho$ but returns only the firm's pledgeable income $y - \Delta$. The shock must be financed via insurance, by pooling with the pledgeable margin of firms that are *not* shocked—the first layer of insurance, operating within the BDC's own portfolio.

At the portfolio level, widespread-shock states are precisely those in which the need for cross-subsidy is largest and the capacity to supply it is smallest. The BDC is therefore insured against these states by being pooled with other BDCs: the bank's credit lines move resources across BDCs in different states. Compared with the direct-lending benchmark, layering is *neutral* absent BDC insolvency costs: interposing a finitely diversified BDC between firms and the diversified bank costs nothing, even though the BDC bears genuine portfolio risk

that the bank does not. Undiversified risk alone does not compromise insurance—when $\lambda < \hat{\lambda}$, the BDC simply passes widespread-shock states through to the committed line, chooses $m^* = n$, and replicates the benchmark.

Funding one more draw can push the BDC across its insolvency boundary and trigger the portfolio-level deadweight cost $n\lambda$. Because this cost is binary, capacity matters by changing the set of default states rather than the depth of the shortfall within a state already in default. When this friction is high, insurance is partial along the credit chain.

We emphasize two points about restricting contracts to bank debt rather than allowing general contracts. First, under direct lending it is without loss: the bank's diversified portfolio makes its resources and collections deterministic, so a state-contingent contract is degenerate, and bank debt implements the constrained-efficient allocation as in Holmström and Tirole (1998). In the chain the same restriction bites. A fixed face value prevents the bank from transferring resources into widespread-shock states—for example, through state-contingent debt relief priced ex ante—which would eliminate the deadweight loss altogether and restore full insurance. We focus on bank debt as the empirically relevant contract space: the bank credit lines to BDCs in our data are standard senior secured facilities.

The prediction of partial coverage ($m^* < n$), together with the ex-post rationing it implies in widespread-shock states ($k > m^*$), constitutes the empirical content of the model; Section 5 confronts both implications with the data.

### 4.3.2 Comparison with Direct Lending

Compared with *unregulated* direct lending, the chain provides less insurance: from (5) and (11),

$$W^B(0) - W^N(m^*) = (y - R\rho)\,\mathbb{E}[k - \min\{k, m^*\}] + n\lambda q_n(m^*) \;\geq\; 0, \tag{14}$$

the sum of foregone continuations and expected insolvency losses. The chain is nonetheless selected because direct lending is regulated: it dominates when $W^N(m^*) \geq W^B(\kappa_B)$, which, when the regulated bank would still fully insure, reduces to a threshold on the regulatory wedge,

$$R + e\kappa_B \;\geq\; \frac{ny - np\lambda - W^N(m^*)}{n(1+p\rho)}. \tag{15}$$

The market thus selects the arrangement that provides *less* liquidity insurance: the regulatory saving on the funding side exceeds the insurance lost on the asset side.

### 4.3.3 Implementation: Credit Lines to Individual Firms

We have so far treated the BDC and its firms as a bundle. We now show that the allocation is implemented by the contracts observed in practice—a term loan and a credit line to each firm.

At $t = 0$, each firm receives a term loan of 1 and a credit line with limit $\rho$ at promised gross rate $R_N$. Consider the case in which the BDC has full bargaining power. Since a firm can pledge at most $y - \Delta$, the highest feasible promise is

$$R_N = y - \Delta, \tag{16}$$

and this rate is also optimal: it maximizes the BDC's pledgeable cash flow state by state, which minimizes the BDC's default probability.

The resulting cash flows are exactly those of the bundle. An unshocked firm repays $R_N = y - \Delta$ in full. A shocked and funded firm owes $R_N(1+\rho) > y - \Delta$, defaults, and turns over its pledgeable income $y - \Delta$. A shocked and unfunded firm is liquidated and repays nothing. Collections in state $k$ are therefore $(y - \Delta)\,[n - k + \min\{k, m\}]$, reproducing (4).

The implemented contracts make the two-layer structure of insurance concrete. Through

the credit lines it extends, the BDC provides the first layer, pooling liquidity risk across its borrower firms. Undiversified liquidity shocks nonetheless remain—owing to the BDC's small portfolio size and the concentration of its commitment book documented in Section 3.2—and constitute the BDC's own liquidity risk; the committed bank credit line insures the BDC across these states, forming the second layer.

The market implementation reveals one friction we neglect: the BDC bears no separate penalty when it fails to fund all borrower draws upon $k > m$. Our implications are robust to adding such a penalty as long as it is reasonably smaller than $n\lambda$—justified because the bank facility is senior secured debt whose default destroys franchise value for both the BDC and its manager's other funds.

Finally, bargaining power determines how surplus is divided between the BDC and its firms, and with it the BDC's debt capacity. Full bargaining power lets the BDC capture all pledgeable income, making insolvency least likely; weaker bargaining power leaves more rent with firms, thins the BDC's collections, and raises the bank rate and BDC defaults. These effects are quantitative: partial insurance survives under any fixed division of surplus in which rationing coverage still spares the BDC insolvency in widespread-shock states.

## 4.4 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.

### 4.4.1 Firm Liquidity Management in the Credit Chain

The market implementation—layered credit lines—carries a further implication for firms' liquidity management. Suppose at $t = 0$ each firm $i$ can reduce its probability $p_i$ of a liquidity shock through an unobservable effort at an increasing, convex cost $c(1 - p_i)$. In a symmetric decentralized equilibrium, each firm's choice $p^{eq}$ ($eq$ for decentralized $eq$uilibrium) satisfies

$$-c'(1 - p^{eq}) = -(y - R_N) + \Delta\, \gamma(m; p^{eq}), \tag{17}$$

where $\gamma(m; p^{eq}) \equiv \mathbb{E}\Big[\min\Big\{1, \frac{m}{k}\Big\}\Big]$ is the probability that a shocked firm is funded. Shirking saves the effort cost but raises the chance of a liquidity shock, which forfeits the profit $y - R_N$ and leaves the firm its continuation payoff $\Delta$ only if funded, with probability $\gamma(m; p^{eq}) \leq 1$.

However, each firm ignores that its own draw crowds out coverage for the other firms sharing the same liquidity pool. To see this externality, a planner instead maximizes portfolio firms' joint payoff:

$$\max_{(p_i)_{i=1}^n} \sum_{i=1}^{n} \Big[(1 - p_i)(y - R_N) + p_i\, \gamma_i(m; p_{-i})\, \Delta - c(1 - p_i)\Big].$$

Relative to the individual firm's problem, the planner's first-order condition adds a crowding-out wedge—a higher exposure by firm $i$ raises the chance that the pool's capacity binds, which lowers the coverage $\gamma_j$ of every other firm $j$:

$$-c'(1 - p^{planner}) = -(y - R_N) + \Delta\, \gamma(m; p^{planner}) + \underbrace{\Delta \sum_{j \neq i} p^{planner}\, \frac{\partial \gamma_j}{\partial p_i}\bigg|_{p_i = p^{planner}}}_{\leq 0}.$$

Because each firm ignores this externality, equilibrium effort in liquidity management is inefficiently low.

**Proposition 2.** *Suppose the bank credit line capacity satisfies* $0 < m^* < n$. *Then firms inefficiently shirk in liquidity management in the decentralized equilibrium:* $p^{eq} > p^{planner}$. *When* $m^* = n$, *the equilibrium and planner choices coincide.*

When $0 < m^* < n$, liquidity insurance is constrained: bank credit line is a common liquidity pool that the BDC's borrowers draw on in widespread-shock states, and it is precisely the constrained provision that turns each firm's private liquidity choice into an externality on the others. Therefore, the externality is specific to liquidity provision by nonbanks, where constrained coverage arises from concentrated portfolios and insolvency costs related to lack of government backstop. In contrast, bank credit lines provide full coverage ($m^* = n$) and the externality vanishes, as the second part of Proposition 2 shows.

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.[13]

### 4.4.2 Aggregate Liquidity Risk

Aggregate risk can be introduced by allowing the shock probability to depend on a common state $Z$. Conditional on $Z$, firm shocks remain independent and

$$k_j \mid Z \sim \text{Binomial}(n, p_Z). \tag{18}$$

Diversification eliminates idiosyncratic risk at the bank, but its total drawdowns and collections still vary with $Z$—aggregate liquidity risk remains on the bank balance sheet.

[13]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.

The bank's funding layer is irrelevant in the baseline: its diversified portfolio is riskless, so any investor finances it at the outside return $R$. The introduction of aggregate risk makes this layer relevant: the investors who fund the bank now care about the states in which its cash flows arrive. Define the bank's net revenue per BDC in state $Z$ as

$$\pi_B(Z; m, R_I) \equiv \mathbb{E}^{\mathbb{P}}[(R_I - R)\,(n + \rho \min\{k, m\}) + \min\{0, \Pi_k(m, R_I)\} \mid Z]\,. \tag{19}$$

Equation (19) captures the bank's physical cash flows under the physical distribution $\mathbb{P}$. The risk-adjusted pricing kernel enters only through the participation constraint.

Suppose first that the bank is market funded. Its marginal investors value payoffs most in aggregate bad states, when consumption is low and marginal utility is high. Let $M(Z)$ denote this marginal value, normalized so that $\mathbb{E}[M] = 1$. Competition then requires the bank's cash flows to break even from these investors' perspective:

$$\mathbb{E}[M(Z)\,\pi_B(Z; m)] = 0 \quad \Longleftrightarrow \quad \mathbb{E}^{\mathbb{Q}}[\pi_B(Z; m)] = 0. \tag{20}$$

In an aggregate high-draw state, many BDCs draw simultaneously and bank collections deteriorate precisely when investors' marginal utility is high. Losses in these states therefore require greater compensation to support a given capacity. Market funding thus makes aggregate liquidity insurance expensive when it is most valuable and, as aggregate risk grows, potentially unviable. This is the rational-investor benchmark of Holmström and Tirole (1998).

Deposits provide a flatter funding margin because they supply transaction services, are insured, and may flow into banks during market stress (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006). Let $\omega \in [0, 1]$ denote the deposit-funded share, with the remainder

financed by market-priced capital. In reduced form, the Bank PC becomes

$$\mathbb{E}^{\mathbb{P}}[(\omega + (1-\omega)M(Z))\,\pi_B(Z;m)] = 0. \tag{21}$$

Deposits mute only the covariance premium attached to losses in aggregate bad states, so a larger deposit-funded share lowers that premium when bank net revenue is negatively correlated with $M$.

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.

# 5 Evidence on Model Implications

The model yields two implications that we take to the data. First, the BDC may optimally choose a bank credit line with undrawn capacity smaller than the unfunded commitments extended to its borrowers ($m^* < n$): liquidity insurance is *partial* if the BDC faces relatively high insolvency costs. Second, partial insurance implies *ex-post rationing*: in states where realized borrower liquidity shocks exceed the BDC's bank credit capacity ($k > m^*$), the BDC cannot accommodate all drawdown requests. Borrower drawdowns are therefore rationed precisely when widespread liquidity needs hit a BDC whose liquidity backstop is small relative to its commitment book. This section tests the two implications in turn.

## 5.1 Partial Liquidity Insurance

We first examine the cross-sectional relationship between the credit commitments a BDC extends to its borrowers and those it receives from banks.[14] Specifically, we regress the quantity of a BDC's bank credit line(s) on the BDC's total unfunded commitment to borrowers in its commitment book, controlling for the BDC's lagged total assets, cash and equivalents, and total debt, all scaled by lagged total assets. We also control for a dummy for the BDC's public status, which is associated with a different equity funding structure. The regressions include different sets of fixed effects to account for time and BDC-level heterogeneity.

Table 9 reports the results. Columns 1–3 and 4–6 use the total bank credit limit and the undrawn amount as the dependent variables, respectively. Across all columns, the coefficient on total unfunded commitment is positive and statistically significant, indicating that BDCs with larger commitments to borrowers also maintain larger bank credit lines. The magnitudes indicate partial coverage: in the most stringent specifications (columns 3 and 6), a one-dollar increase in unfunded commitments is associated with about \$0.92 of additional bank credit line capacity, out of which roughly \$0.54 is undrawn, which is lower than what full insurance ($m^* = n$) would require. This estimated gap is likely a conservative evidence of the model's prediction because in addition to managing commitment books, BDCs also use bank credit lines for other liquidity needs, such as genreral investment acticities (Internet Appendix Section IA.10 and Table IA.4).

## 5.2 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 accommo-

[14] The sample consists of BDC-quarters with a bank credit line, consistent with the model's focus on BDCs that use bank credit lines as a liquidity backstop.

date 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 ($k$) exceeds the liquidity it has ($m^*$). 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 liquidity-stressed BDCs 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, $-\Delta \,\text{Unfunded}_t/\text{Unfunded}_{t-1}$, as in Section 3.2. Motivated by facts in Section 3.2.3, 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 relatively high leverage (lagged Debt/EBITDA of at least four). This measure captures variation in the borrower's liquidity needs associated with aggregate and industry-specific shocks. We also construct a measure of the BDC's *Liquidity Stress*, defined as the ratio of its total unfunded commitments to the sum of its cash and undrawn bank credit. This measure captures the BDC's ability to accommodate borrower drawdowns.

To test the implication, we regress the borrower's realized drawdown on the interaction of Industry Peer Drawdown and the BDC's Liquidity Stress. 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 stress.

Table 10 reports the results. In column 1, the interaction of Industry Peer Drawdown with the continuous Liquidity Stress is negative and significant: borrower drawdowns of more stressed BDCs become less sensitive to their industry peers' drawdowns. Columns 2–4 replace the continuous BDC Liquidity Stress with indicators for stress exceeding 100%, 120%, and 150%, respectively. The point estimates' magnitude increases with the severity of stress: 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, the evidence is consistent with partial insurance: BDCs with insufficient liquidity ration borrower drawdowns ex post.

# 6 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 three empirical patterns. BDCs' credit commitments have grown quickly during recent years, faster than both total BDC assets and banks' credit commitments. BDCs' commitment book is concentrated and its borrowers' draws are correlated, leaving

undiversified liquidity risks at the BDC level. BDCs cover 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—a prediction the data bear out both in levels, where undrawn bank credit backs unfunded commitments well below dollar-for-dollar, and ex post, where liquidity-stressed BDCs accommodate less of their borrowers' industry draw pressure. Second, this constrained provision yields a novel externality in firms' liquidity management: each firm exerts inefficiently little effort because it ignores how its own draw on the shared pool crowds out the others—a tragedy of the commons specific to nonbanks' constrained liquidity provision.

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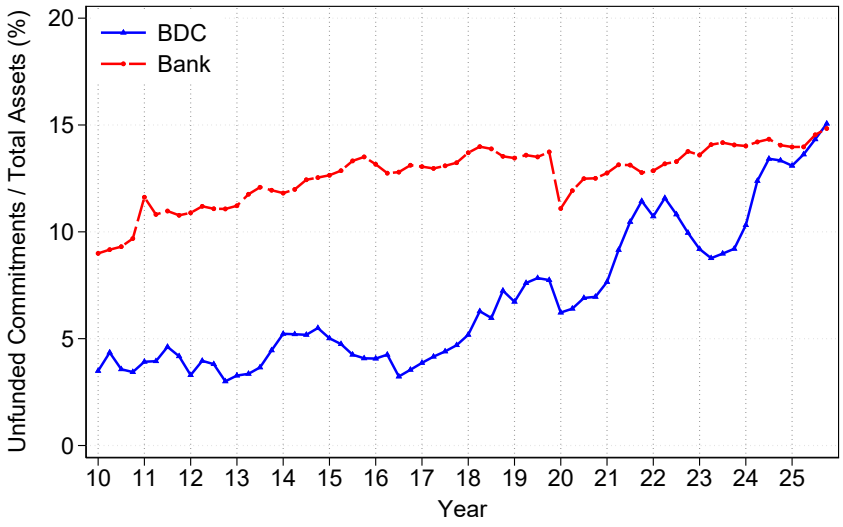
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**(a)** Aggregate time trend, 2010Q1–2025Q4




**(b)** Cross-sectional distribution at 2025Q4

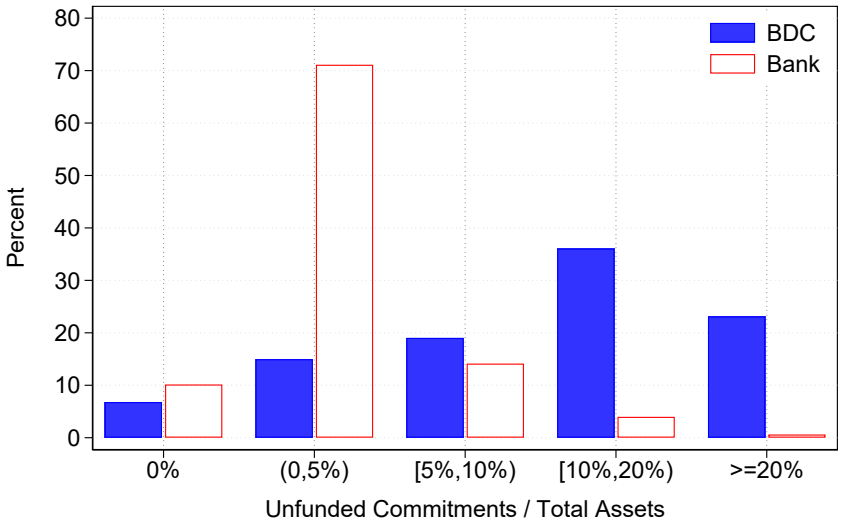



**Figure 1. Liquidity Provided by Intermediaries: BDCs vs Banks.**
This figure shows liquidity insurance provided by BDCs and banks to their corporate borrowers, measured as unfunded commitments divided by total assets. For BDCs, the numerator is total unfunded commitments. For banks, the numerator is the sum of "unused commitments" (Call Report Schedule RC-L) to commercial and industrial (C&I) borrowers and to financial institutions. Panel (a) plots quarterly aggregate ratios across all banks and all BDCs from 2010Q1 to 2025Q4. Panel (b) presents the cross-sectional distribution at 2025Q4. Data sources: SEC's EDGAR and FFIEC's Consolidated Reports of Condition and Income.

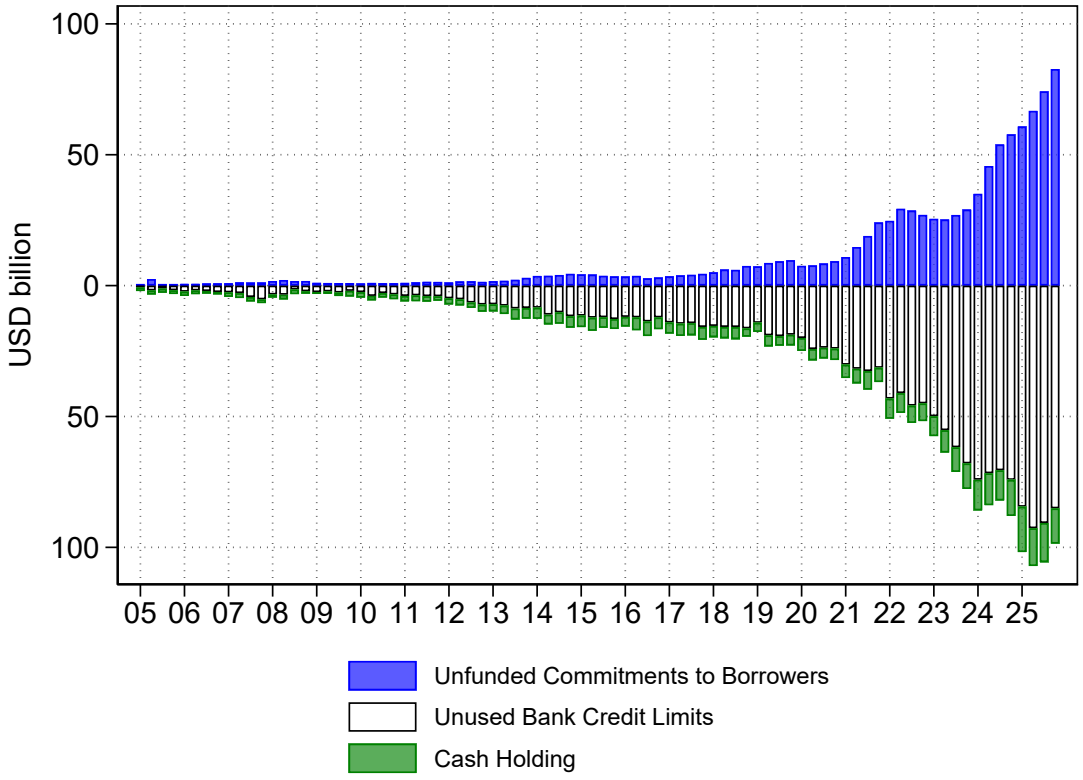
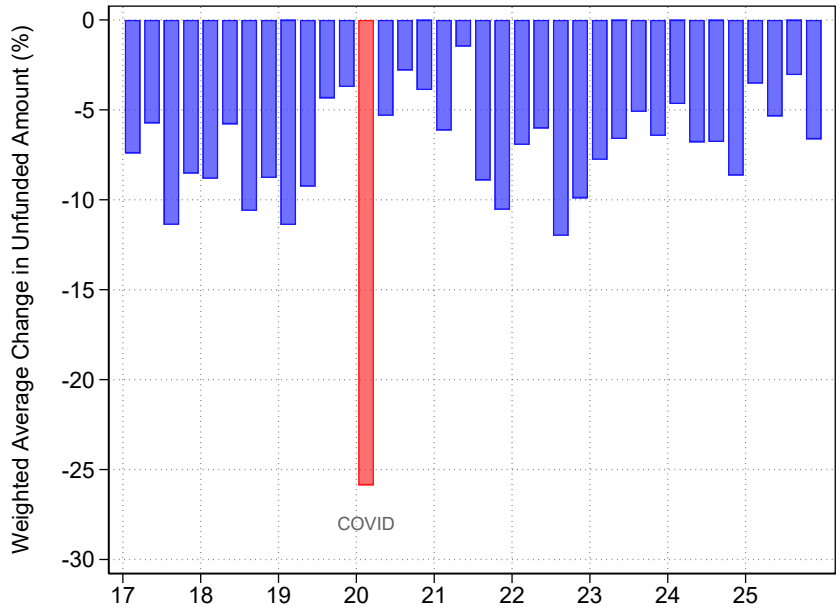



**Figure 2. Liquidity Provided by and Available to BDCs.**
This figure presents quarterly aggregate amounts of unfunded commitments provided by BDCs—undrawn by portfolio companies—and the undrawn commitment available to them between 2005Q1 and 2025Q4. The blue bars show the dollar amount of unfunded loan 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 show BDCs' total cash holdings. Solid red and dashed grey lines indicate the number of BDCs that have unfunded loan commitments and undrawn bank credit lines, respectively. Data sources: SEC EDGAR, Compustat, and S&P Capital IQ.

**(a)** %ΔUnfunded




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

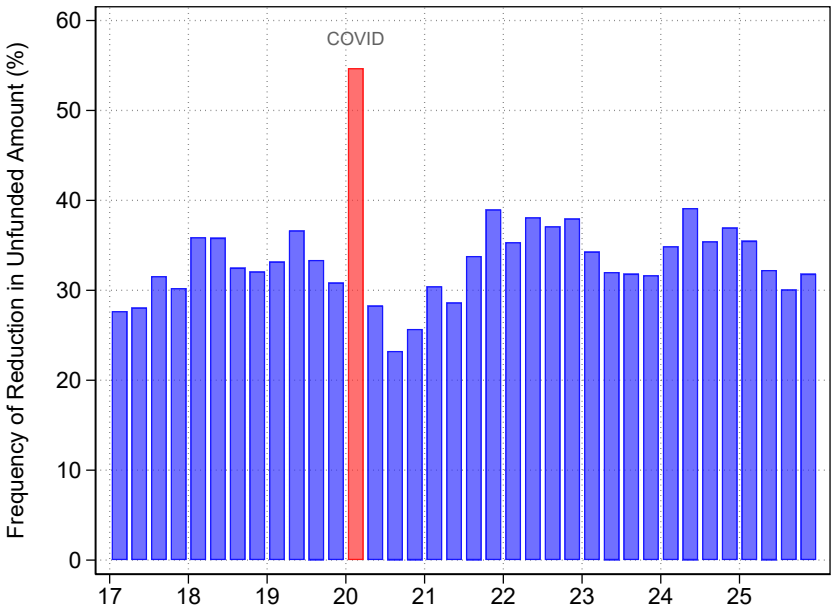



**Figure 3. Changes in Unfunded Commitments.**
This figure presents the time series of changes in unfunded commitments extended by BDCs to their borrowers from 2017Q1 to 2025Q4. Panel (a) shows the average quarterly percentage change in unfunded commitment amounts. Panel (b) displays the quarterly frequency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

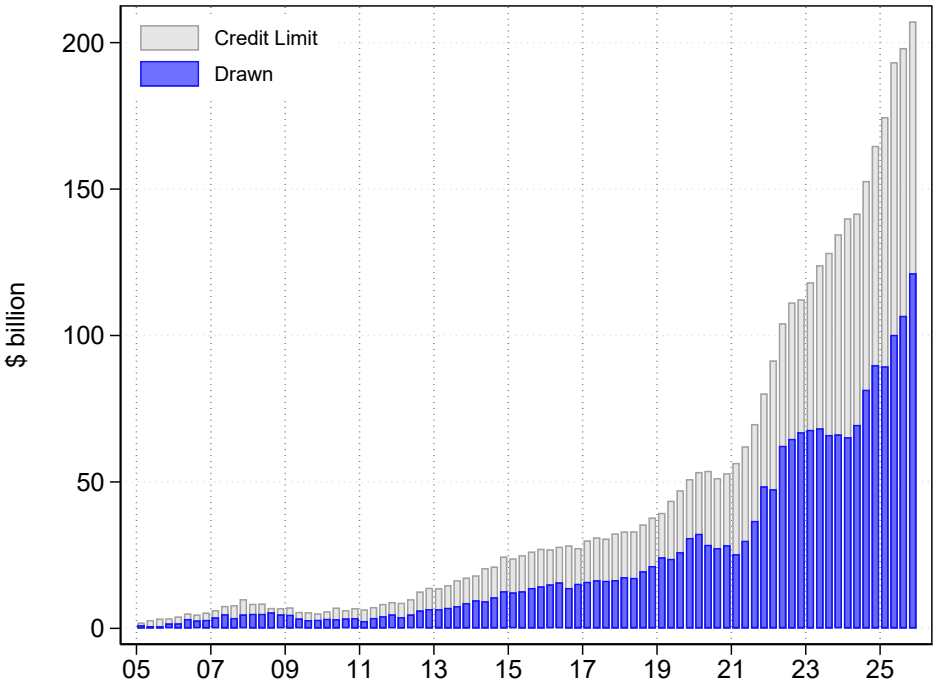



**Figure 4. BDC Credit Lines from Banks: Credit Limits and Drawn Amounts.** This figure plots aggregate bank credit line capacity (gray) and drawn amounts (blue) across all BDCs by quarter from 2005Q1 to 2025Q4. Credit lines are revolving facilities that BDCs obtain from banks to fund their lending and 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.

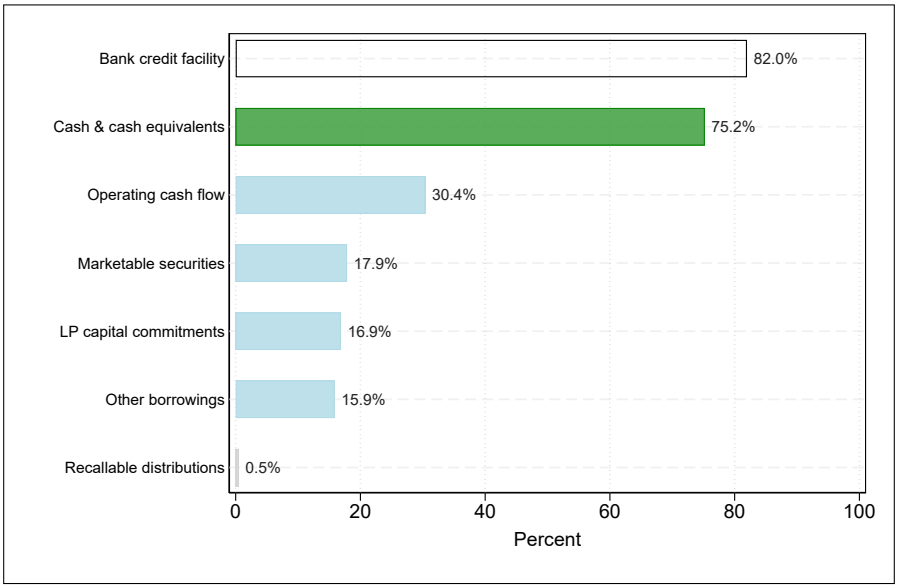



**Figure 5. Liquidity Sources Disclosed as Backstop for Unfunded Commitments.** This figure reports the share of BDC 10-K filings in which the BDC discusses specific sources of liquidity as backstop for its unfunded commitments to portfolio companies. The sample is restricted to the 605 10-K filings in which the BDC explicitly names at least one specific source of liquidity as backstop for unfunded commitments. Internet Appendix Figure IA.2 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. 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 individual portfolio commitments. *Mean Unfunded* and *Median Unfunded* are the within-BDC-quarter average and median amounts of undrawn credit commitment 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.

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| *Panel A: All BDC-Quarters* | | | | | | | | |
| Total Assets | 6,435 | 1,593.4 | 4,171.7 | 21.2 | 201.3 | 523.6 | 1,454.7 | 6,005.5 |
| Total Debt | 6,435 | 694.8 | 1,966.6 | 0.0 | 38.0 | 205.6 | 641.8 | 2,364.1 |
| Equity | 6,435 | 850.7 | 2,198.9 | 11.7 | 121.6 | 287.4 | 790.9 | 3,306.3 |
| Cash | 6,435 | 59.8 | 140.0 | 0.4 | 5.6 | 19.7 | 56.9 | 246.4 |
| Total Unfunded | 6,435 | 149.8 | 551.3 | 0.0 | 2.0 | 22.7 | 118.8 | 546.8 |
| N Bank Credit Lines | 6,435 | 1.5 | 1.6 | 0.0 | 1.0 | 1.0 | 2.0 | 4.0 |
| Bank Credit Limit | 6,435 | 590.8 | 1,484.1 | 0.0 | 1.8 | 190.0 | 600.0 | 2,035.0 |
| Undrawn Bank Credit | 6,435 | 270.3 | 704.5 | 0.0 | 0.0 | 75.0 | 249.0 | 1,100.0 |
| *Panel B: BDC-Quarters with Reported Unfunded Commitment Book* | | | | | | | | |
| N Commitments | 3,749 | 47.1 | 63.2 | 1.0 | 7.0 | 21.0 | 63.0 | 175.0 |
| Mean Unfunded | 3,748 | 4.1 | 7.0 | 0.4 | 1.1 | 2.4 | 4.8 | 11.9 |
| Median Unfunded | 3,748 | 2.9 | 6.4 | 0.2 | 0.8 | 1.6 | 3.2 | 9.2 |
| *Panel C: BDC-Quarter with Portfolio Holdings* | | | | | | | | |
| Senior Secured Loans | 5,811 | 73.6% | 31.9% | 0.0% | 65.8% | 87.4% | 96.9% | 100.0% |
| Joint Ventures | 5,811 | 0.8% | 3.0% | 0.0% | 0.0% | 0.0% | 0.0% | 5.5% |
| Equity | 5,811 | 11.8% | 20.2% | 0.0% | 1.0% | 4.8% | 12.7% | 59.5% |
| Other Debt | 5,811 | 13.7% | 23.7% | 0.0% | 0.0% | 2.4% | 14.5% | 77.3% |

## Table 2. Summary of Unfunded Commitment Book 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 amount of undrawn credit commitment. $\Delta$*Unfunded* and % $\Delta$*Unfunded* are the change and percentage change in the unfunded amount from the previous period, respectively. $\mathbf{1}(\Delta \textit{Unfunded} < 0)$ 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 | -0.396 | 5.672 | -3.700 | -0.295 | 0.000 | 0.000 | 1.072 |
| % $\Delta$Unfunded | 82,476 | -0.028 | 0.361 | -0.540 | -0.084 | 0.000 | 0.000 | 0.316 |
| $\mathbf{1}(\Delta\text{Unfunded} < 0)$ | 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 | -0.080 | 2.879 | -1.670 | -0.001 | 0.000 | 0.000 | 1.080 |
| % $\Delta$Unfunded | 28,839 | -0.003 | 0.304 | -0.417 | 0.000 | 0.000 | 0.000 | 0.334 |
| $\mathbf{1}(\Delta\text{Unfunded} < 0)$ | 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 | -0.704 | 7.971 | -5.944 | -0.627 | 0.000 | 0.000 | 0.310 |
| % $\Delta$Unfunded | 21,731 | -0.059 | 0.385 | -0.617 | -0.151 | 0.000 | 0.000 | 0.064 |
| $\mathbf{1}(\Delta\text{Unfunded} < 0)$ | 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 $\ell$, $\sigma_\ell$ is the time-series standard deviation of its quarterly liquidity shock from the commitment book, estimated as the dollar-weighted percentage change in unfunded commitments across continuing borrowers, $\Delta u_{i,\ell,t}/u_{i,\ell,t-1}$. The dollar-valued liquidity shock associated with a one-standard-deviation quarterly change in unfunded commitments 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. Rows 2–4 split the sample into terciles by the ratio of Total Unfunded to Total Assets. $\mathbf{1}(\widehat{\sigma}^{\$}_{\ell t} > \text{Cash})$ is an indicator for whether the estimated shock exceeds lagged cash.

| | $N$ | Median Total Unfunded/TA | Median $\widehat{\sigma}^{\$}_{\ell t}$/Cash | Mean $\mathbf{1}(\widehat{\sigma}^{\$}_{\ell t} > \text{Cash})$ |
|---|---|---|---|---|
| | (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 3,236 BDC-quarters with data on both the commitment book and portfolio holdings. 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.

| | Commitment Book | | | | Loan Portfolio | | | | Diff |
|---|---|---|---|---|---|---|---|---|---|
| | mean | p25 | p50 | p75 | mean | p25 | p50 | p75 | (paired-$t$) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | | | | *HHI* | | | | | |
| Industry | 0.296 | 0.163 | 0.225 | 0.356 | 0.161 | 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 | 0.235 | 0.060 | 0.132 | 0.317 | 0.059 | 0.026 | 0.037 | 0.063 | 0.175*** |
| | | | | *Top-3 Share* | | | | | |
| 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 | 0.828 | 0.414 | 0.321 | 0.374 | 0.466 | 0.222*** |
| Sponsor | 0.569 | 0.311 | 0.525 | 0.837 | 0.268 | 0.171 | 0.221 | 0.321 | 0.301*** |
| N | | | | 3,236 | | | | | |

## Table 5. 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 over-weighted bucket within the BDC-quarter; Top-3 sums the weights of the three largest over-weighted buckets. The sample consists of 3,236 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. 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.

| | Commitment Book | | | | Loan Portfolio | | | | Diff |
|---|---|---|---|---|---|---|---|---|---|
| | mean | p25 | p50 | p75 | mean | p25 | p50 | p75 | (paired-$t$) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Industry Excess Share* | | | | | | | | | |
| 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*** |
| *HQ State Excess Share* | | | | | | | | | |
| Top-1 | 0.277 | 0.120 | 0.217 | 0.364 | 0.105 | 0.052 | 0.077 | 0.119 | 0.172*** |
| Top-3 | 0.455 | 0.259 | 0.416 | 0.621 | 0.215 | 0.124 | 0.173 | 0.255 | 0.240*** |
| *Sponsor Excess Share* | | | | | | | | | |
| Top-1 | 0.309 | 0.118 | 0.223 | 0.428 | 0.117 | 0.056 | 0.085 | 0.139 | 0.192*** |
| Top-3 | 0.536 | 0.277 | 0.492 | 0.800 | 0.243 | 0.138 | 0.196 | 0.296 | 0.293*** |
| N | 3,236 | | | | | | | | |

## Table 6. 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*** | 0.175*** | 0.074*** |
| | (0.037) | (0.031) | (0.020) |
| Sponsor Backed | 0.046*** | 0.033*** | 0.009 |
| | (0.013) | (0.011) | (0.006) |
| M&A Deal | 0.055*** | 0.026*** | 0.036*** |
| | (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) | (0.002) | (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) | (0.006) |
| Industry-Year-Quarter FEs | Y | Y | Y |
| HQ State-Year-Quarter FEs | Y | Y | Y |
| BDC-Year-Quarter FEs | Y | Y | Y |
| $N$ | 306,323 | 274,883 | 274,883 |
| $R^2$ | 0.377 | 0.411 | 0.265 |

## Table 7. 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 2010Q1–2024Q4. The dependent variable is either the continuous shock $\Delta u_{i,\ell,t}/u_{i,\ell,t-1}$ or the binary shock $\mathbf{1}\{\Delta u_{i,\ell,t} < 0\}$. In Panel A, the regresors 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: | $[0,2)$ | $[2,4)$ | $\geq 4$ | $< 0$ |
|---|---|---|---|---|
| | (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: | $\Delta$BBB | $\Delta$HY | SP500 | $\Delta$VIX |
|---|---|---|---|---|
| | (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 8. Variance Decomposition of Liquidity Shocks from Commitment Books**

This table reports $R^2$s 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 $u_{i,\ell,t-1} > \$1$ 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 $\Delta u_{i,\ell,t}/u_{i,\ell,t-1}$ or the binary shock $\mathbf{1}\{\Delta u_{i,\ell,t} < 0\}$; OLS columns weight all observations equally, WLS columns use $u_{i,\ell,t-1}$ as weights.

| | %ΔUnfunded | | $\mathbf{1}$(ΔUnfunded $< 0$) | |
|---|---|---|---|---|
| | 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 9. Relationship Between Unfunded Commitments and Bank Credit Lines

This table regresses the amount of bank credit lines on the BDC's total unfunded commitment to borrowers in its commitment book. The sample consists of 4,742 BDC-quarters in 2005Q1–2025Q4 with a bank credit line. In columns 1–3 the dependent variable is the BDC's total bank credit line limit summed across facilities, scaled by lagged total assets; in columns 4–6 it is the undrawn bank credit limit, also scaled by lagged total assets. The regressor Total Unfunded/$\text{TA}_{t-1}$ sums the unfunded commitments the BDC has extended to borrowers in its commitment book, scaled by lagged total assets; *Public* is an indicator equal to one when the BDC is currently exchange-listed; lagged controls are total debt and cash and equivalents, both scaled by lagged total assets, and log lagged total assets. Columns vary in BDC and year-quarter fixed effects, standard errors are clustered at the BDC level, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Bank Credit Line Capacity / $\text{TA}_{t-1}$**

| | Limit | | | Undrawn | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Total Unfunded / $\text{TA}_{t-1}$ | 1.588*** | 1.000*** | 0.916*** | 1.087*** | 0.608*** | 0.538*** |
| | (0.220) | (0.153) | (0.154) | (0.165) | (0.150) | (0.157) |
| Debt / $\text{TA}_{t-1}$ | 0.520*** | 0.639*** | 0.478*** | 0.027 | 0.161 | 0.012 |
| | (0.137) | (0.128) | (0.154) | (0.095) | (0.107) | (0.118) |
| Cash / $\text{TA}_{t-1}$ | 0.746*** | 0.265 | 0.245 | 0.573*** | 0.271* | 0.253* |
| | (0.234) | (0.179) | (0.171) | (0.181) | (0.156) | (0.146) |
| $\log \text{TA}_{t-1}$ | −0.170*** | −0.365*** | −0.383*** | −0.122*** | −0.260*** | −0.279*** |
| | (0.019) | (0.022) | (0.023) | (0.015) | (0.016) | (0.018) |
| Public | −0.154*** | 0.114** | 0.064 | −0.020 | 0.173*** | 0.114** |
| | (0.040) | (0.055) | (0.062) | (0.027) | (0.046) | (0.051) |
| BDC FEs | N | Y | Y | N | Y | Y |
| Year-Quarter FEs | N | N | Y | N | N | Y |
| $N$ | 4,742 | 4,740 | 4,740 | 4,742 | 4,740 | 4,740 |
| $R^2$ | 0.445 | 0.755 | 0.767 | 0.362 | 0.650 | 0.669 |

## Table 10. BDC Liquidity Stress and Rationing of Borrower Drawdowns

This table reports estimated rationing of borrower drawdown by liquidity-stressed BDCs. The sample is a BDC–borrower–quarter panel of unfunded commitments between 2010Q1–2024Q4. In columns 1–4, the dependent variable is the borrower's net drawdown, proxied by the decrease in its unfunded commitment, $-\Delta \text{Unfunded}_t/\text{Unfunded}_{t-1}$, 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 Stress 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 Stress. Columns 2–4 replace the continuous Liquidity Stress with indicators that Stress 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 | | | | | | |
| × Liquidity Stress$_{t-1}$ | −0.016** | | | | −0.012*** | 0.005 |
| | (0.006) | | | | (0.004) | (0.004) |
| × **1**{Stress > 100%} | | −0.027* | | | | |
| | | (0.015) | | | | |
| × **1**{Stress > 120%} | | | −0.040** | | | |
| | | | (0.016) | | | |
| × **1**{Stress > 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 Model Proofs

It is useful to define the probability of BDC insolvency at capacity $m$:

$$q_n(m) \equiv \Pr(\Pi_k(m, R_I) < 0). \tag{A.1}$$

## A.1 Direct Bank Lending

The participation constraint pins down bank rate for each coverage $s$,

$$R_B(s) = \frac{(R + e\kappa_B)(1 + ps\rho) - ps(y - \Delta)}{1 - p}, \tag{A.2}$$

so a coverage level $s$ is feasible exactly when $R_B(s) \leq y - \Delta$, i.e., when

$$g(s) \equiv (1 - p + ps)(y - \Delta) - (R + e\kappa_B)(1 + ps\rho) \geq 0. \tag{A.3}$$

By Assumption 1, $g'(s) = p[(y - \Delta) - \rho(R + e\kappa_B)] < 0$: each covered shocked firm repays only $y - \Delta$ against the funding cost $\rho(R + e\kappa_B)$ of its draw, so expanding coverage consumes the margin that unshocked firms provide. The feasible set is therefore an interval $[0, \bar{s}]$. When $g(0) > 0 > g(1)$, the cap solves $g(\bar{s}) = 0$, which rearranges to

$$\bar{s}(\kappa_B) = \frac{(1 - p)(y - \Delta) - (R + e\kappa_B)}{p[(R + e\kappa_B)\rho - (y - \Delta)]}; \tag{A.4}$$

$\bar{s} > 0$ requires $R + e\kappa_B < (1 - p)(y - \Delta)$, that is, $s = 0$ satisfies participation. It is straightforward to check that $\frac{d\bar{s}}{d\kappa_B} = \frac{e(1+ps\rho)}{g'(s)} < 0$: the cap declines in the regulatory cost.

In the region $y > (R + e\kappa_B)\rho$, the objective is strictly increasing in $s$ and the optimal coverage is $s^* = \min\{1, \bar{s}(\kappa_B)\}$. When $g(1) \geq 0$, equivalently $y - \Delta \geq (R + e\kappa_B)(1 + p\rho)$,

full insurance obtains and welfare is

$$W^B(\kappa_B) = n\left[y - (R + e\kappa_B)(1 + p\rho) - p\lambda\right], \tag{A.5}$$

In the constrained regime $s^* = \bar{s} < 1$, substituting the binding (A.3) into the objective gives

$$W^B(\kappa_B) = n\,\Delta\,(1 - p + p\bar{s}(\kappa_B)) - np\lambda. \tag{A.6}$$

In both regimes it is easy to check that $\frac{dW^B}{d\kappa_B} < 0$.

## A.2 Proof of Proposition 1

*Proof.* Because the fee implements bank break-even at every capacity, it remains only to characterize default probabilities and compare surplus across capacities. For $k \leq m$, BDC net worth is $(y-\Delta)n - R_I(n+\rho k)$; for $k > m$, it is $(y-\Delta)(n-k+m) - R_I(n+\rho m)$. Hence the continuous insolvency threshold is

$$\hat{k}(m) = \begin{cases} \dfrac{n[(y-\Delta) - R_I]}{y-\Delta} - m\dfrac{R_I\rho - (y-\Delta)}{y-\Delta}, & m < \dfrac{n[(y-\Delta) - R_I]}{R_I\rho}, \\ \dfrac{n[(y-\Delta) - R_I]}{R_I\rho}, & m \geq \dfrac{n[(y-\Delta) - R_I]}{R_I\rho}. \end{cases} \tag{A.7}$$

Assumption 3 implies that the first branch decreases in $m$, while the second is constant. Therefore $q_n(m)$ is weakly increasing in capacity and $q_n(0) = \min_m q_n(m)$. The floor inequality in (13) implies $q_n(0) < q_n(n)$, so at least one capacity below $n$ strictly reduces default probability.

For completeness, the endpoint thresholds are

$$\hat{k}(0) = \frac{n[(y-\Delta) - R_I]}{y-\Delta}, \qquad \hat{k}(n) = \frac{n[(y-\Delta) - R_I]}{R_I\rho}. \tag{A.8}$$

Thus, away from nongeneric integer ties, $q_n(0) < q_n(n)$ exactly when the interval $\left(\hat{k}(n), \hat{k}(0)\right]$ contains an integer realization. Requiring this interval to have length at least one gives the simpler but stronger sufficient condition

$$n \geq \frac{(y-\Delta)R_I\rho}{[(y-\Delta) - R_I][R_I\rho - (y-\Delta)]}. \tag{A.9}$$

In the illustrative calibration $n = 12$, $p = 0.10$, $\rho = 2$, $R_I = 1.02$, $y = 3$, and $\Delta = 1.5$, the right-hand side is 11.8. Capacities $m = 0, 1, 2$ attain the minimum default probability, whereas $m = 3, \ldots, 12$ lie on a higher-default plateau. Productive surplus selects $m = 2$ from the former and $m = 12$ from the latter, so the optimum jumps from full capacity to $m^* = 2$ as $\lambda$ crosses its cutoff.

Raising capacity from $m$ to $m + 1$ continues another project exactly when $k > m$. It changes productive surplus by

$$(y - R\rho)\Pr(k > m) > 0, \tag{A.10}$$

where the inequality follows from Assumption 1. The common firm-default loss $np\lambda$ cancels from this comparison. Hence $m = n$ is the unique optimum at $\lambda = 0$.

For each $m < n$, the difference between surplus at full capacity and at $m$ is

$$W^N(n) - W^N(m) = (y - R\rho)\,\mathbb{E}[k - \min\{k, m\}] - n\lambda\,[q_n(n) - q_n(m)]\,. \tag{A.11}$$

Define

$$\hat{\lambda} \equiv \min_{m<n:\, q_n(m)<q_n(n)} \frac{(y - R\rho)\mathbb{E}[k - \min\{k, m\}]}{n[q_n(n) - q_n(m)]}. \tag{A.12}$$

The set in (A.12) is nonempty by Assumption 3, and every ratio is strictly positive. If $q_n(m) \geq q_n(n)$, both terms in (A.11) favor full capacity. If $q_n(m) < q_n(n)$, full capacity strictly dominates $m$ precisely when $\lambda$ is below the corresponding ratio. Thus $m = n$ uniquely dominates every smaller capacity for $\lambda < \hat{\lambda}$, while for $\lambda > \hat{\lambda}$ at least one smaller capacity strictly dominates $n$.

Finally, among capacities with the same default probability, the largest one strictly dominates because productive surplus increases with capacity. Since the capacity set is finite, for sufficiently large $\lambda$ any capacity with above-minimum default probability is dominated by the largest capacity attaining the minimum. This proves the final claim. □

## A.3 Proof of Proposition 2

*Proof.* Let $X_i \in \{0, 1\}$ be the indicator for whether firm $i$'s idiosyncratic liquidity shock realizes, with $X_i \sim \text{Bernoulli}(p_i)$ independently across firms, and let $K_{-i} \equiv \sum_{\ell \neq i} X_\ell$. Conditional on $X_i = 1$ and $K_{-i} = r$, the fair lottery funds firm $i$ with probability $\min\{1, m/(1 + r)\}$. Define firm $i$'s coverage probability conditional on being shocked as

$$\gamma_i(m; p_{-i}) \equiv \Pr(i \text{ is funded} \mid X_i = 1) = \sum_{r=0}^{n-1} \min\left\{1, \frac{m}{1+r}\right\} \Pr(K_{-i} = r). \tag{A.13}$$

For $j \neq i$, define $K_{-i,-j} \equiv \sum_{\ell \neq i,j} X_\ell$ and $g_m(r) \equiv \min\{1, m/(1 + r)\}$. Independence gives

$$\frac{\partial \gamma_j(m; p_{-j})}{\partial p_i} = \mathbb{E}[g_m(1 + K_{-i,-j}) - g_m(K_{-i,-j})] \leq 0. \tag{A.14}$$

For interior shock probabilities, the inequality is strict exactly when $0 < m < n$: an additional shock then reduces firm $j$'s lottery allocation with positive probability. At $m = 0$ no firm is funded, and at $m = n$ every shocked firm is funded, so the cross-effect is zero at both corners.

*Individual FOC.* Firm $i$ solves

$$\max_{p_i} (1 - p_i)(y - R_N) + p_i \, \gamma_i(m; p_{-i}) \, \Delta - c(1 - p_i), \tag{A.15}$$

taking $p_{-i}$ as given. Because $\gamma_i(m; p_{-i})$ does not depend on $p_i$, the interior FOC is

$$c'(1 - p_i) = (y - R_N) - \Delta \, \gamma_i(m; p_{-i}). \tag{A.16}$$

Under symmetry, $p_i = p$ and $\gamma_i(m; p_{-i}) = \gamma(m; p)$, so

$$c'(1 - p^{eq}) = (y - R_N) - \Delta \, \gamma(m; p^{eq}). \tag{A.17}$$

*Planner's FOC.* A planner maximizing all firms' joint payoff internalizes the capacity constraint. Let $K = \sum_i X_i$. Because exactly $\min\{K, m\}$ shocked projects are funded, the planner solves

$$\max_{(p_i)_{i=1}^n} \sum_{i=1}^{n} \left[ (1 - p_i)(y - R_N) - c(1 - p_i) \right] + \Delta \, \mathbb{E}[\min\{K, m\}] \, . \tag{A.18}$$

Changing $X_i$ from zero to one raises $\min\{K, m\}$ by one exactly when $K_{-i} < m$. Hence

$$\frac{\partial}{\partial p_i} \mathbb{E}[\min\{K, m\}] = \Pr(K_{-i} < m), \tag{A.19}$$

and the planner's interior FOC is

$$c'(1-p_i) = (y - R_N) - \Delta \Pr(K_{-i} < m). \tag{A.20}$$

*Comparison.* Under symmetry, the planner's FOC becomes

$$c'(1-p^{planner}) = (y - R_N) - \Delta \Pr\Big(\text{Binomial}(n-1, p^{planner}) < m\Big). \tag{A.21}$$

For any symmetric interior $p$, equation (A.13) gives

$$\gamma(m;p) - \Pr(\text{Binomial}(n-1,p) < m) = \mathbb{E}\left[\frac{m}{1+K_{-i}}\mathbf{1}\{K_{-i} \geq m\}\right]. \tag{A.22}$$

The right-hand side is strictly positive when $0 < m < n$ and $p \in (0,1)$. Thus, at any common exposure, an individual firm values insurance by its probability of being funded, including in rationed states, whereas the planner values an additional shock only when it increases the total number of funded projects. Because $c'$ is strictly increasing, $c'(1-p)$ is strictly decreasing in $p$; both right-hand sides of (A.17) and (A.21) are weakly increasing in $p$. Equation (A.22) therefore implies $p^{planner} < p^{eq}$ for interior solutions whenever $0 < m < n$.

If $m = n$, both coverage terms equal one, so the two FOCs coincide. If $m = 0$, both equal zero and the two FOCs also coincide. Applying these results at $m = m^*$ proves the proposition. □

# Internet Appendix

"Credit Commitments by Nonbanks"

## IA.7. Data Collection and Processing

This section provides details on sample construction. Section IA.7.1 defines the universe of BDCs and their regulatory filings. Sections IA.7.2–IA.7.5 describe each group of variables collected from those filings: total unfunded commitments, borrower-level commitment books, bank credit lines, balance-sheet items, and statement-of-cash-flow items. Section IA.7.6 describes the linking of borrowers in BDC commitment books to PitchBook companies. Section IA.7.7 describes the FFIEC Call Report data on banks.

### IA.7.1. Universe of BDCs from SEC EDGAR

We identify the universe of business development companies 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 public BDC list 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 "ghost" CIKs that appear on SEC lists with no corresponding 10-K/10-Q filings are dropped as data-entry artifacts. 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.7.2–IA.7.5 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 public 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.[1] Figure IA.4 shows the growth of the two public BDC segments 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.7.2. 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.7.3. Unfunded Credit 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

[1] Private BDCs that elect 1940 Act BDC status without registering under the Exchange Act file no periodic reports with the SEC and are therefore outside the scope of our sample.

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.7.2). The dataset we collect covers 2,989 BDC-quarters and 138,456 facility-level observations within our 2005Q1–2025Q4 sample window.

### IA.7.4. 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 (the maximum permitted limit increase). 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.7.5. 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.7.6. Identifying Borrowers in Unfunded Commitment Books

The unfunded commitment book data in Section IA.7.3 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 funded 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 non-trivial share of borrowers even when the underlying firm is in 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 we match the FactSet record to a PitchBook record on a composite key of (par value, maturity, base rate, 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.7.7. 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.8. Measurement of Credit Facility Drawdown

### IA.8.1. 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 $\%\Delta u$ or generate $\%\Delta u = -1$. We additionally restrict the sample to BDC-borrower-quarters with lagged unfunded commitment above $1 million. The restriction avoids small-denominator noise in $\%\Delta u$. The threshold matches the analogous filter applied to S&P Capital IQ public-firm drawdowns in Section IA.8.2.

We measure the borrower's liquidity shock with two alternative measures. The continuous shock is the percentage change in unfunded commitment, $\%\Delta u_{i,\ell,t} = \Delta u_{i,\ell,t}/u_{i,\ell,t-1}$, winsorized at the 1st and 99th percentiles. The binary shock is the indicator $\mathbf{1}\{\Delta u_{i,\ell,t} < 0\}$. The continuous measure helps quantify the magnitude of drawdown, while the binary mea-

sure 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 $\Delta u$ 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 $\Delta u$ 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 $\Delta u = -\Delta\text{funded}$ holds exactly, with a sample correlation of $-1.000$.

### IA.8.2. Public-Firm Drawdown Factors from S&P Capital IQ

Regressions in Table 7 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 ($[0, 2)$, $[2, 4)$, $\geq 4$, and a negative-EBITDA bucket). For each bucket and quarter, we compute the dollar-weighted average drawdown (weighting by lagged drawn balance). The resulting four quarterly time series are the factors used in columns 1–4 of Table 7, Panel A.

## IA.9. Bank Credit Lines: Composition, Events, and Robustness

This appendix documents the bank credit line data underlying Section 3.3 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.7 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.

Table IA.8 reports the contractual events on these facilities: of 6,584 events, amendments are the most common, and amendments overwhelmingly upsize credit limits and extend maturities —facilities ratchet up as BDCs scale. Table IA.9 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 30% above the base credit limit.

Finally, Table IA.5 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 administra-

tive 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.10. 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 3.3 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.6 illustrates the scale of borrower drawdowns in a concrete case: Ares Capital's commitment book around the 2020Q1 COVID stress.

We estimate the association between the BDC's liquidity needs and its bank credit line activities. In column 1 of Table IA.3, 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

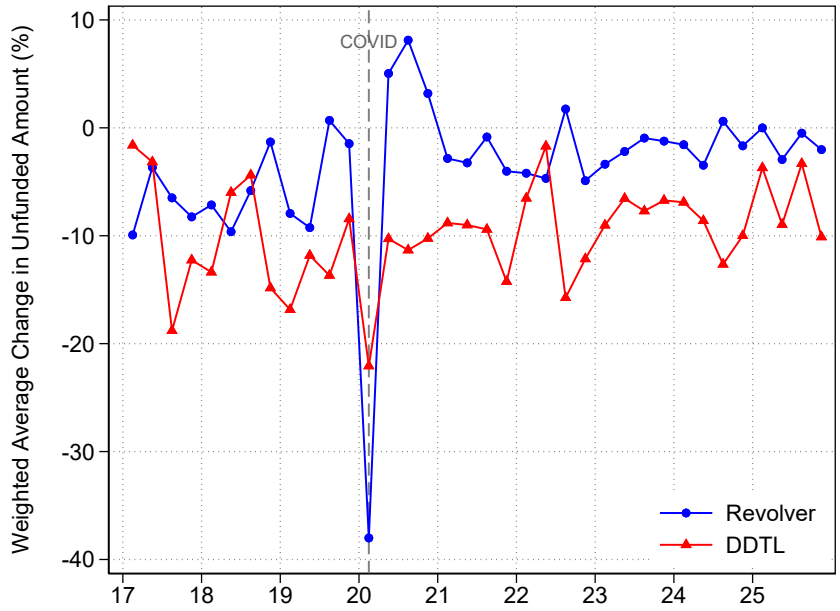
[2]The facility-level measure in Section 3.2 is not subject to this confounding: the sample is restricted to continuing facilities with at least $1M lagged unfunded (Internet Appendix IA.8.1), which isolates drawdown activity from origination and termination effects.

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 20 cents per dollar of incremental investment cash outflow.[3] Table IA.2 reports summary statistics for the variables used in these regressions.

[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.4 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.

**(a)** %ΔUnfunded




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

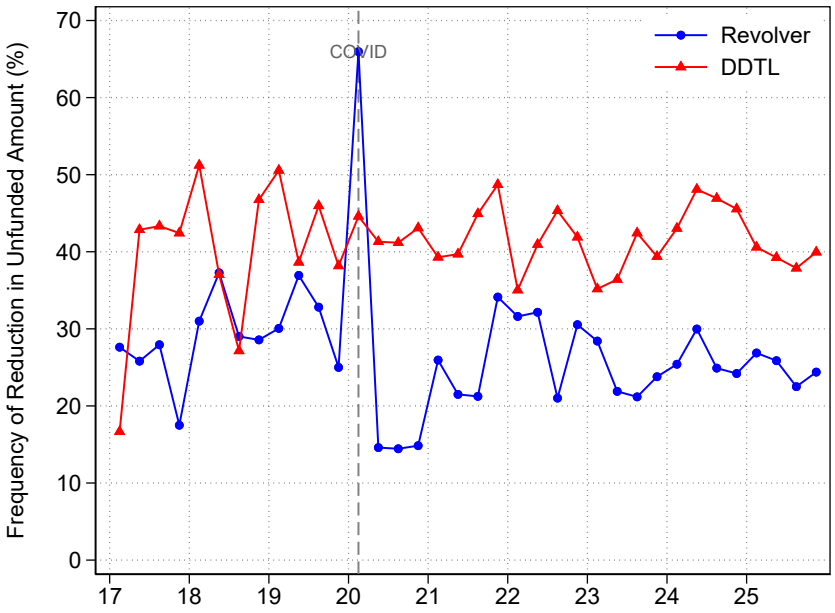



**Figure IA.1. Changes in Unfunded Commitments by Commitment Type.** This figure presents the time series of changes in unfunded commitments extended by BDCs to their borrowers from 2017Q1 to 2025Q4, categorized by commitment type (Revolver and DDTL). Panel (a) shows the average quarterly percentage change in unfunded commitment amounts for each type. Panel (b) displays the quarterly frequency of reductions in unfunded commitment amounts. The vertical dashed line marks the onset of the COVID-19 pandemic.

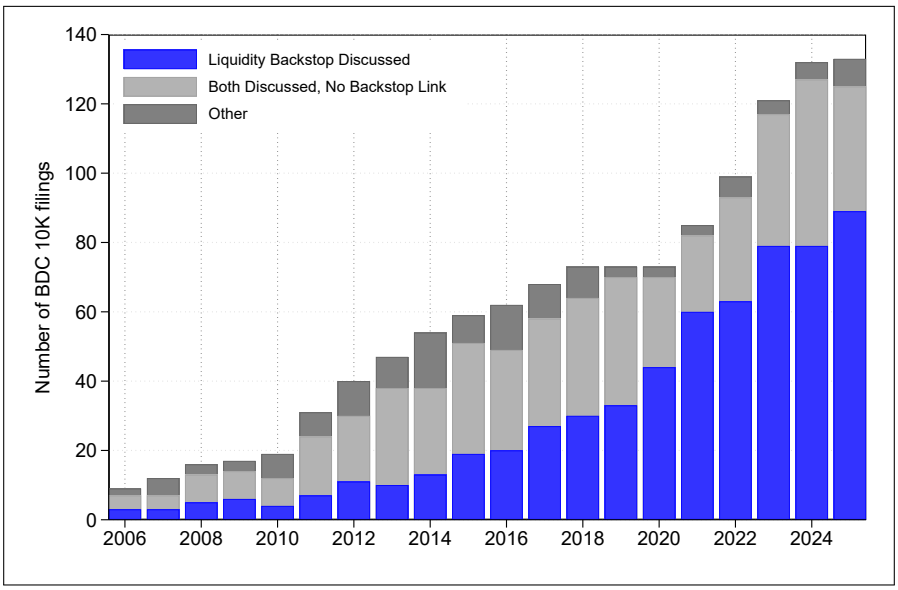



**Figure IA.2. Disclosure of Liquidity-Backstop Discussion in BDC 10-K Filings.** This figure plots the number of BDC 10-K filings in each year by disclosure status. The sample comprises 1,243 10-K filings, each classified into one of three categories. "Liquidity Backstop Discussed" marks filings in 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.

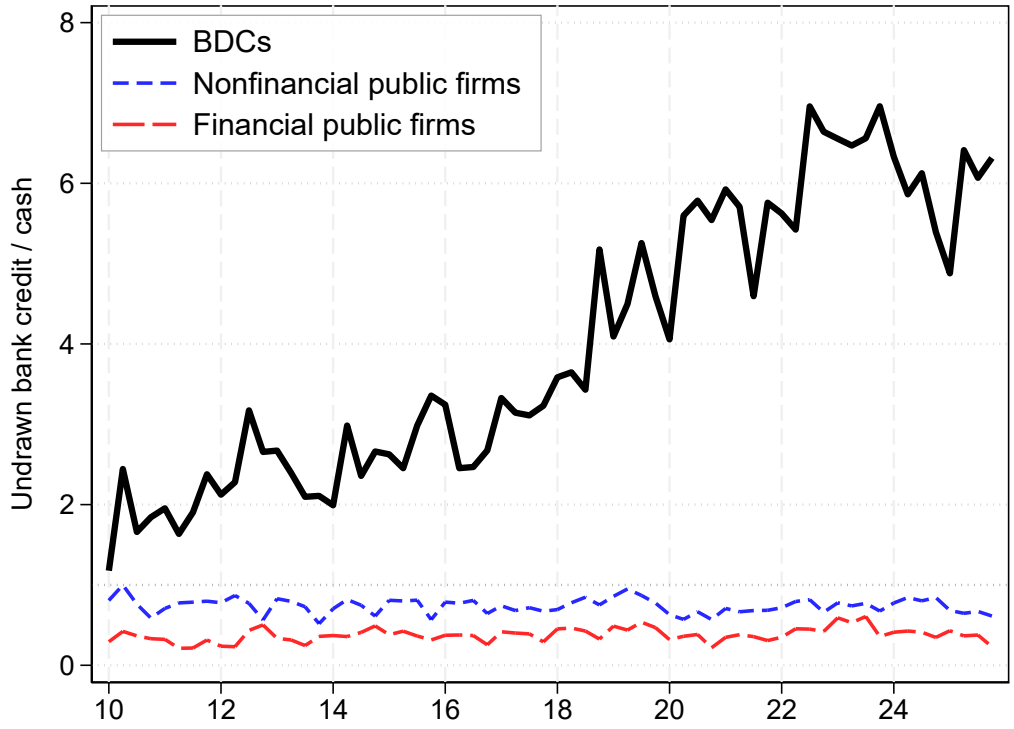



**Figure IA.3. Undrawn Bank Credit to Cash Ratio: BDCs vs. Public Firms.** This figure plots the quarterly aggregate ratio of undrawn bank credit line capacity to cash and cash equivalents, separately for the BDC sector (hand-collected from EDGAR), nonfinancial public firms (Compustat S&P Capital IQ, SIC outside 6000–6999), and financial public firms (SIC 6000–6999). Within each sector and quarter, the numerator is the sum of undrawn capacity (credit limit − outstanding) across all firms that report a credit-line limit, and the denominator is the sum of cash and cash equivalents across the same firms. Firm-quarters with reported undrawn capacity exceeding total assets are dropped as data errors. The dotted horizontal line at one separates regimes in which undrawn capacity exceeds cash from those in which cash exceeds undrawn capacity. The median quarterly ratio is 3.43 for the BDC sector, 0.76 for nonfinancial public firms, and 0.37 for financial public firms. BDCs therefore hold roughly four times the undrawn-to-cash ratio of nonfinancial public firms and nine times that of financial public firms over the same period, indicating that bank credit lines are a much larger component of the BDC sector's immediate liquidity buffer than at public firms. Data sources: SEC's EDGAR (BDCs); S&P Capital IQ Capital Structure and Compustat quarterly (public firms).

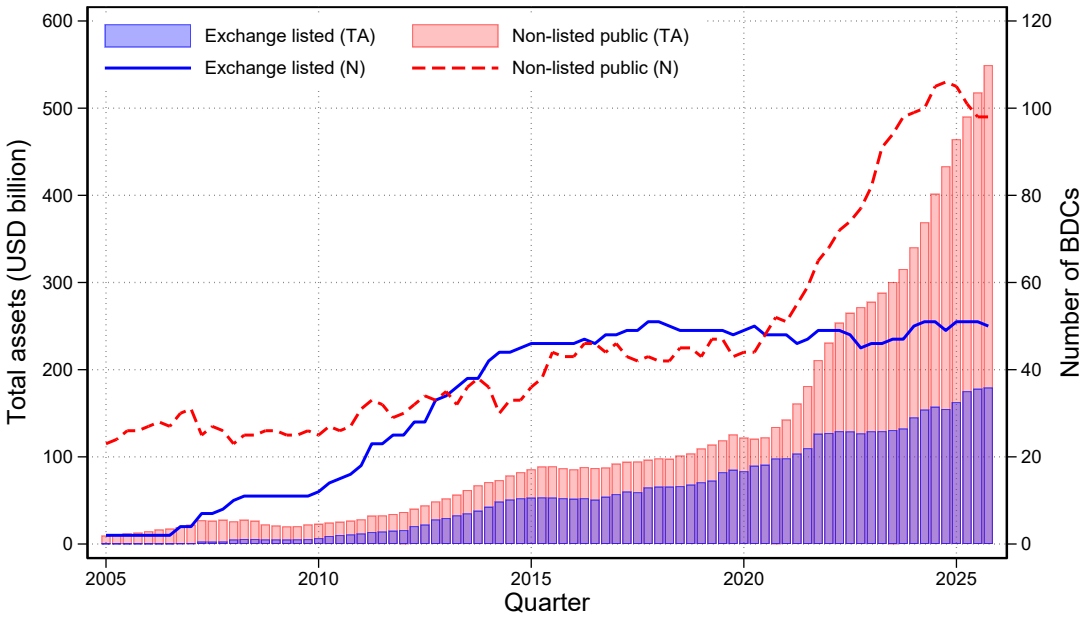



**Figure IA.4. BDCs by Listing Status: Number and Total Assets.**
This figure plots the BDC universe between 2005Q1 and 2025Q4 by listing status. The stacked bars (left axis) show total assets (USD billion) summed across BDCs in each segment per quarter, with exchange-listed BDCs at the bottom (blue) and non-listed public 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.

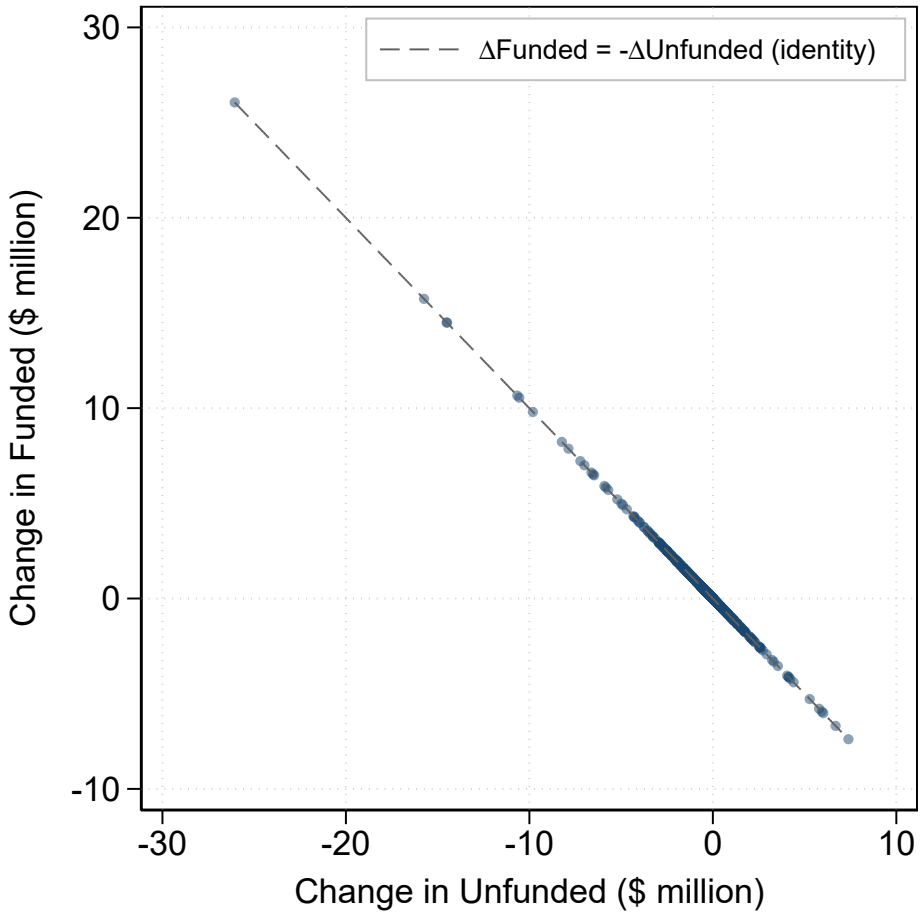



**Figure IA.5. Change in Unfunded Commitment as a Proxy for Drawdown.** This figure plots quarterly changes in unfunded commitments against changes in funded commitments at the BDC–portfolio company level, within the subsample where the BDC's total commitment to the borrower is unchanged between consecutive 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.

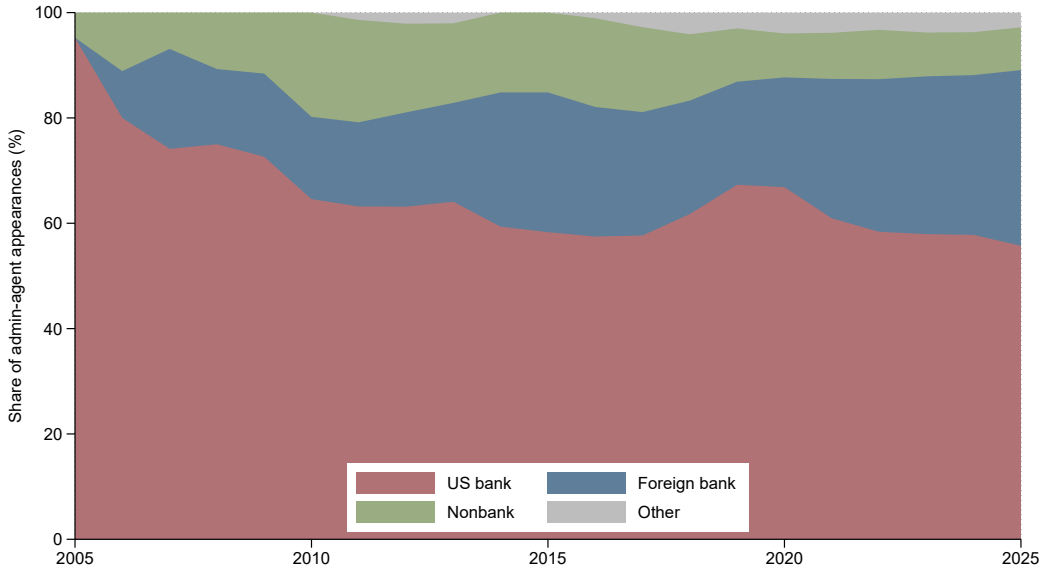



**Figure IA.6. Admin-Agent Composition Over Time.**
This figure plots the share of admin-agent appearances on BDC credit lines by lender type at annual frequency over 2005–2025, as a stacked area chart. The four buckets match Table IA.7: US bank, Foreign bank (foreign-headquartered banks operating in 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).

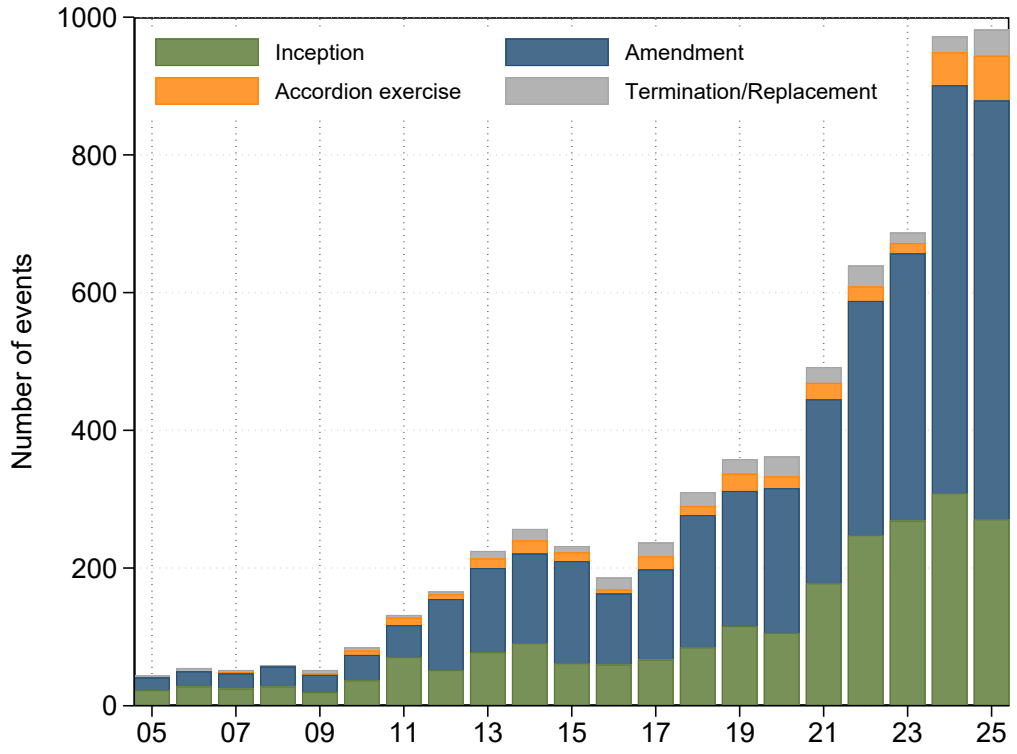



**Figure IA.7. Bank Credit Line Events Over Time.**
This figure plots the annual count of bank credit line events extracted from BDC 10-K and 10-Q filings, 2005–2025, stacked by event type: inception, amendment, accordion exercise, and termination/replacement (terminations and replacements are pooled).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

## 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 percentage change in unfunded commitment, $\Delta u_{i,\ell,t}/u_{i,\ell,t-1}$; the binary shock is the indicator $\mathbf{1}\{\Delta u_{i,\ell,t} < 0\}$. For each BDC $\ell$, $\mu_\ell$ and $\sigma_\ell$ are the time-series mean and standard deviation of BDC $\ell$'s own shock series (dollar-weighted across its continuing borrowers in the continuous case, equal-weighted in the binary case). $\sigma_\ell^{\text{BMK}}$ is the time-series standard deviation of the diversified-benchmark shock computed over the same quarters as BDC $\ell$. Each row reports the cross-sectional distribution across the 79 BDCs. The BDC-level volatility $\sigma_\ell$ feeds the magnitude estimates in Table 3 of the paper.

| | $\Delta$Unfunded | | | | $\mathbf{1}(\Delta\text{Unfunded} < 0)$ | | | |
|---|---|---|---|---|---|---|---|---|
| | $\mu_\ell$ (1) | $\sigma_\ell$ (2) | $\sigma_\ell^{\text{BMK}}$ (3) | $\sigma_\ell/\sigma_\ell^{\text{BMK}}$ (4) | $\mu_\ell$ (5) | $\sigma_\ell$ (6) | $\sigma_\ell^{\text{BMK}}$ (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 | −0.102 | 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 | −0.049 | 0.140 | 0.052 | 3.694 | 0.441 | 0.156 | 0.067 | 4.217 |

## Table IA.2. Summary Statistics for Liquidity-Response Regressions

This table reports summary statistics for the variables used in Table IA.3 and Table IA.4. The sample is the common BDC-quarter estimation sample after absorbing BDC and time fixed effects. Variables scaled by assets are divided by lagged total assets. All scaled variables are winsorized at the 1st and 99th percentiles within the pre-FE common sample, matching the regression specifications; log assets are not winsorized.

| Variable | $N$ | Mean | SD | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| *Panel A. Investment demand and bank credit line response* | | | | | | |
| Inv. cash outflow / $\text{TA}_{t-1}$ | 3,755 | 0.205 | 0.244 | 0.067 | 0.128 | 0.239 |
| Bank credit line drawdown / $\text{TA}_{t-1}$ | 3,755 | 0.025 | 0.099 | -0.010 | 0.000 | 0.046 |
| Bank credit line amendment / $\text{TA}_{t-1}$ | 3,755 | 0.013 | 0.060 | 0.000 | 0.000 | 0.000 |
| Bank credit line inception / $\text{TA}_{t-1}$ | 3,755 | 0.035 | 0.132 | 0.000 | 0.000 | 0.000 |
| Bank credit line termination / $\text{TA}_{t-1}$ | 3,755 | 0.014 | 0.065 | 0.000 | 0.000 | 0.000 |
| *Panel B. Other funding sources* | | | | | | |
| Inv. proceeds / $\text{TA}_{t-1}$ | 3,755 | 0.092 | 0.146 | 0.034 | 0.068 | 0.113 |
| Equity issue / $\text{TA}_{t-1}$ | 3,755 | 0.060 | 0.154 | 0.000 | 0.001 | 0.063 |
| Dist. cut / $\text{TA}_{t-1}$ | 3,755 | 0.013 | 0.017 | 0.007 | 0.012 | 0.016 |
| Cash use / $\text{TA}_{t-1}$ | 3,755 | -0.004 | 0.069 | -0.015 | -0.001 | 0.013 |
| *Panel C. Controls* | | | | | | |
| Undrawn bank credit line / $\text{TA}_{t-1}$ | 3,755 | 0.196 | 0.209 | 0.053 | 0.151 | 0.266 |
| Debt / $\text{TA}_{t-1}$ | 3,755 | 0.377 | 0.170 | 0.309 | 0.419 | 0.491 |
| Cash / $\text{TA}_{t-1}$ | 3,755 | 0.063 | 0.091 | 0.015 | 0.029 | 0.068 |
| $\log \text{TA}_{t-1}$ | 3,755 | 6.533 | 1.539 | 5.739 | 6.581 | 7.503 |

## Table IA.3. 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. The sample is BDC-quarters in 2005Q1–2025Q4 with all five cash-budget levers, the four facility-level outcomes, the regressor, and the lagged controls non-missing (the same sample as Table IA.4). The dependent variables are constructed at the facility level from the as-borrower bank credit-line panel and aggregated to the BDC-quarter: 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, identical to Table IA.4. Lagged controls are undrawn bank credit line capacity, total debt, cash and equivalents, and log assets, all scaled by lagged total assets where relevant. All specifications include BDC and year-quarter fixed effects, standard errors are clustered at the BDC level, and $^{*}$, $^{**}$, $^{***}$ represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: $\Delta$ Bank Credit Line Capacity $/ \mathbf{TA}_{t-1}$**

| | Drawdown (1) | Amendment (2) | Inception (3) | Termination (4) |
|---|---|---|---|---|
| Inv. Cash Outflow $/ \mathrm{TA}_{t-1}$ | 0.103*** | 0.037*** | 0.059** | -0.014 |
| | (0.016) | (0.008) | (0.025) | (0.010) |
| Undrawn Bank Credit $/ \mathrm{TA}_{t-1}$ | 0.139*** | -0.039*** | -0.081*** | 0.064*** |
| | (0.019) | (0.009) | (0.027) | (0.014) |
| Debt $/ \mathrm{TA}_{t-1}$ | -0.128*** | 0.019 | -0.107*** | -0.014 |
| | (0.024) | (0.012) | (0.038) | (0.016) |
| Cash $/ \mathrm{TA}_{t-1}$ | 0.006 | -0.007 | 0.009 | -0.001 |
| | (0.029) | (0.019) | (0.050) | (0.019) |
| $\log \mathrm{TA}_{t-1}$ | -0.001 | -0.003 | -0.029*** | -0.003 |
| | (0.004) | (0.002) | (0.007) | (0.003) |
| BDC FEs | Y | Y | Y | Y |
| Year-Quarter FEs | Y | Y | Y | Y |
| $N$ | 3,755 | 3,755 | 3,755 | 3,755 |
| $R^2$ | 0.303 | 0.182 | 0.237 | 0.234 |

## Table IA.4. BDC Liquidity Needs and Other Sources of Liquidity

This table decomposes BDC investment cash demand across the four non-bank-credit-line funding levers, regressing each lever on the same investment-demand regressor and controls. The CL drawdown response is reported separately in Table IA.3 as part of the bank credit line decomposition. The sample is the same BDC-quarters in 2005Q1–2025Q4 as Table IA.3. Each column reports a separate regression for one funding lever, signed so positive values are sources of funds: investment proceeds from sales and principal repayments, equity issuance, distribution cuts, and balance-sheet cash use; all four levers 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, ordered by economic importance and all scaled by lagged total assets where relevant. All specifications include BDC and year-quarter fixed effects, standard errors are clustered at the BDC level, and *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Funding Amount / $\mathbf{TA}_{t-1}$**

| | Inv. proceeds (1) | Equity issue (2) | Dist. cut (3) | Cash use (4) |
|---|---|---|---|---|
| Inv. cash outflow / $\mathrm{TA}_{t-1}$ | $0.290^{***}$ | $0.270^{***}$ | 0.003 | $-0.037^{***}$ |
| | (0.036) | (0.030) | (0.004) | (0.013) |
| Undrawn bank credit line / $\mathrm{TA}_{t-1}$ | $-0.094^{***}$ | $-0.074^{***}$ | $-0.006^{***}$ | $0.057^{***}$ |
| | (0.020) | (0.019) | (0.002) | (0.013) |
| Debt / $\mathrm{TA}_{t-1}$ | −0.010 | $0.125^{***}$ | $-0.016^{***}$ | −0.001 |
| | (0.032) | (0.036) | (0.005) | (0.022) |
| Cash / $\mathrm{TA}_{t-1}$ | $-0.136^{***}$ | 0.060 | −0.006 | $0.287^{***}$ |
| | (0.042) | (0.060) | (0.005) | (0.038) |
| $\log \mathrm{TA}_{t-1}$ | $-0.016^{**}$ | $-0.079^{***}$ | $-0.004^{***}$ | $0.029^{***}$ |
| | (0.007) | (0.007) | (0.001) | (0.005) |
| BDC FEs | Y | Y | Y | Y |
| Year-Quarter FEs | Y | Y | Y | Y |
| $N$ | 3,755 | 3,755 | 3,755 | 3,755 |
| $R^2$ | 0.441 | 0.633 | 0.328 | 0.207 |

## Table IA.5. 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 9 and IA.3: 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.

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

| | RegionalExposure $\times\mathbf{1}\{t = j\}$ | | LowTier1Exposure $\times\mathbf{1}\{t = j\}$ | |
|---|---|---|---|---|
| Horizon $t$ | (1) | (2) | (3) | (4) |
| $t = -4$ | -0.494 | -0.451 | -0.391 | -0.389 |
| | (0.377) | (0.380) | (0.363) | (0.351) |
| $t = -3$ | -0.299 | -0.378 | -0.318 | -0.357 |
| | (0.251) | (0.230) | (0.244) | (0.231) |
| $t = -2$ | -0.186 | -0.184 | -0.266 | -0.245 |
| | (0.180) | (0.184) | (0.195) | (0.195) |
| $t = -1$ | 0.079 | 0.057 | 0.015 | 0.021 |
| | (0.052) | (0.039) | (0.041) | (0.040) |
| $t = +1$ | -0.076 | -0.127 | -0.107$^{*}$ | -0.110 |
| | (0.079) | (0.097) | (0.065) | (0.071) |
| $t = +2$ | -0.104 | -0.152 | -0.119 | -0.118 |
| | (0.095) | (0.111) | (0.079) | (0.086) |
| $t = +3$ | -0.052 | -0.117 | -0.021 | -0.027 |
| | (0.125) | (0.139) | (0.114) | (0.116) |
| $t = +4$ | 0.077 | 0.042 | 0.102 | 0.111 |
| | (0.155) | (0.162) | (0.135) | (0.126) |
| BDC FEs | Y | Y | Y | Y |
| Year-Quarter FEs | Y | Y | Y | Y |
| Controls $\times t$ | N | Y | N | Y |
| $N$ | 765 | 765 | 765 | 765 |
| Within $R^2$ | 0.015 | 0.069 | 0.011 | 0.067 |

## Table IA.6. Illustrative Case: Ares Capital's Commitment Book Around the 2020Q1 COVID Stress

This table illustrates borrower drawdowns in the unfunded commitment book of Ares Capital—the BDC with the largest single-quarter unfunded drawdown in our sample—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. 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 |

## Table IA.7. 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, canonicalized to a 173-entity reference table, and aggregated into four economically meaningful 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: Wells Fargo Securities, Morgan Stanley Senior Funding, Citigroup Global Markets, BofA Securities, Goldman Sachs Lending Partners, Truist Securities, and similar US-bank subsidiaries are folded into US bank; BNP Paribas Prime Brokerage and CIBC World Markets are folded into Foreign bank; KKR Capital Markets and other independent broker-dealers are folded into Nonbank. 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 | 2,363 | 2,070 |
| Nonbank | 33 | 1,136 | 867 |
| Other | 15 | 264 | 220 |
| Total | 171 | 11,006 | 7,968 |

**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 | 561 |
| ING Capital LLC | Nonbank | 23 | 26 | 518 |
| Citibank, N.A. | US bank | 26 | 36 | 480 |
| Sumitomo Mitsui Banking Corporation | Foreign bank | 31 | 44 | 436 |
| 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.8. 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 (parsed from the recorded old- and new-value strings for numeric terms, with maturity and revolving-period columns denoting extension versus shortening), and direction is not applicable for categorical fields such as benchmark, lender syndicate, subsidiary borrower, covenants, and facility name. Time-series patterns in event composition are reported in Figure IA.7.

**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.9. 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 base 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 (CLID identifiers) 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 accordion-having CLIDs for which both values are extracted with consistent units (latest values per CLID, normalized to $millions, with plausibility filter $[0.5, 20]$ applied to drop unit-mismatch outliers).

**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 |