Indirect Credit Supply: How Bank Lending to Private Credit Shapes Monetary Policy Transmission*

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Abstract

This paper examines how banks' financing of nonbank lenders affects monetary policy transmission. Using supervisory bank loan-level data and deal-level private credit data, we document the rise of an intermediation chain: Banks lend to Business Development Companies (BDCs)—large players in private credit market—which then lend to firms. As monetary tightening restricts bank lending, firms turn to BDCs for credit, prompting BDCs to borrow more from banks. However, this intermediation chain raises borrowing costs, as banks charge BDCs higher rates, which BDCs pass on to firms. Consistent with this pass-through, bank-reliant BDCs respond more strongly to monetary tightening. Overall, bank lending to nonbanks mitigates credit supply contraction during tightening, but amplifies monetary transmission by increasing borrowing costs.

Keywords: Banks and nonbanks; Monetary policy transmission; Business development companies (BDCs); Private credit; Credit chain

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1 Introduction

Bank lending is central to how monetary policy shapes the real economy (Bernanke and Blinder, 1988; Kashyap and Stein, 2000). When monetary policy tightens, banks typically cut lending and raise borrowing costs, leading to a contraction in credit supply. However, the rise of nonbank lenders—particularly in private credit—has introduced new dynamics into monetary transmission. According to Preqin, private credit has been one of the fastest-growing segments of the U.S. financial system, with total assets reaching $1.1 trillion by 2023, a tenfold increase since 2009.[1] While prior research has explored nonbanks' role in monetary transmission, less is known about how their interactions with banks affect credit availability and borrowing costs during tightening cycles.

This paper fills the gap by studying how banks' financing of nonbank lenders shapes monetary policy transmission. Specifically, we focus on bank lending to Business Development Companies (BDCs)—a rapidly growing segment of the private credit market that primarily lends to large and middle-market firms.[2] BDCs provide an ideal setting to study how monetary policy transmits through bank-nonbank interactions: (i) they operate like banks by originating credit to firms, but unlike banks, they do not have access to deposits, and instead partially rely on bank credit lines to finance their lending activity, effectively extending the intermediation chain. (ii) BDCs are required to disclose detailed portfolio information on a quarterly basis, allowing us to merge deal-level BDC investment data with regulatory bank loan-level data and trace the full credit supply chain. To the best of our knowledge, this is the first paper to study the flow of credit from banks to BDCs and ultimately to firms, and its implications for monetary policy transmission.

We begin our analysis using the Federal Reserve's supervisory Y-14 dataset, which provides detailed loan-level data on bank loans to both private and publicly listed U.S. firms.[3] We document several novel facts about banks' financing of BDCs. First, BDCs' re-

[1] We use 'private credit', 'private debt', and 'direct lending' interchangeably to refer to loans originated and held by nonbank lenders. The growth of private credit likely stems from tighter bank regulation, an expansion of private equity, and demand for more flexible loan products (Block, Jang, Kaplan and Schulze, 2024; Erel and Inozemtsev, 2022).

[2] BDCs are closed-end investment funds. As of 2023, BDCs have more than $310 billion in total assets, making them a significant component of the nonbank lending sector.

[3] The Y-14 dataset is an administrative, matched bank-firm-loan level dataset collected by the Federal

liance on bank credit has grown significantly, more than doubled after the 2022 monetary tightening cycle relative to pre-2021 levels. Second, nearly 90 percent of bank lending to BDCs takes the form of credit lines, which tend to be larger in size and more frequently collateralized than loans to other corporate borrowers.

We document how banks reallocate credit toward BDCs during the 2022 tightening cycle by comparing aggregate lending patterns to BDCs versus other borrowers. We focus on the 2022 cycle due to its unprecedented speed and magnitude of rate hikes and the resulting slowdown in bank credit growth.[4] First, while overall bank loan commitments slowed, lending to BDCs accelerated, and BDCs' credit-line utilization remained steady as non-BDC utilization declined. Second, banks charged BDCs a greater rate premium during tightening, amplifying borrowing costs downstream. These patterns suggest that BDCs play a key role in monetary policy transmission by absorbing indirect credit supply from banks and passing on higher funding costs to firms.

To quantify these patterns, we run regressions to estimate how bank loans to BDCs respond to monetary tightening relative to other loans. To control for credit risk, we use granular internal credit ratings from banks and compare loans of the same rating, issued by the same bank, at the same time. We find that, during the 2022 monetary tightening cycle, banks increased lending to BDCs relative to non-BDC borrowers. The effects are economically significant: loan commitments to BDCs grew 1.1 percentage points more, and their credit-line utilization rose 18.6 percentage points more than that of non-BDC borrowers. Banks also charged BDCs significantly higher rates, with the interest rate premium reaching 1.1 percentage points, adding $0.3 billion in annual loan expenses—15% of their total bank loan costs. While our main focus is on the 2022 monetary tightening, our results remain robust across various monetary policy measures, including changes in the effective Federal Funds rate and monetary policy shocks identified by Jarociński and Karadi (2020) and Bauer and Swanson (2023).

Reserve since 2011 as part of the Dodd-Frank Act Stress Tests. It offers the most detailed coverage of U.S. firms with bank loans, including loan characteristics, credit risk metrics, and borrower financials.

[4]Unlike the gradual 2015–2018 tightening, where rates rose 225 basis points over three years amid continued loan expansion, the 2022 cycle saw a 525 basis point increase in just 18 months, triggering a sharp deceleration in bank credit supply (see the Federal Reserve's H.8 data). This likely increased reliance on private credit, while liquidity pressures and deposit outflows made secured lending to BDCs more attractive.

A key channel for banks reallocating credit to BDCs during monetary tightening is the renegotiation of existing credit lines. Our analysis reveals that BDC borrowers actively renegotiate for higher commitments, with loan commitments rising 4.7 percentage points more than those of other borrowers on credit lines that saw limit expansions. Notably, BDC borrowers also increase credit line drawdowns sharply, particularly on expanded credit lines. These findings highlight coordination between banks and BDC borrowers: as BDCs draw more from their existing credit lines, banks accommodate increased demand by raising credit limits on the most utilized loans, underscoring the role of renegotiation in credit reallocation during monetary contractions.

The simultaneous increase in the quantity and price of bank credit to BDC borrowers suggests heightened demand. But why do banks prefer lending to BDCs over directly lending to firms? We find that profitability—rather than risk-taking—drives this preference through two key channels. First, during monetary tightening, loans to BDCs offer higher returns while carrying lower risk due to greater collateralization, seniority, and lower loss given default (LGD). Second, banks may benefit from lower capital requirements on senior collateralized credit facilities extended to BDCs, further enhancing the appeal of lending to BDCs over direct corporate lending, particularly during monetary tightening.[5]

To examine BDCs' lending strategy during monetary tightening, we focus on overlapping borrowers—firms that hold both bank loans and BDC credit. Using a Khwaja and Mian (2008)-style identification strategy, which compares loans within the same borrower, quarter, and loan type, we find that BDC loans carry a rate premium of nearly 1.5 percentage points during tightening. This premium remains robust after controlling for borrower risk and loan seniority, ruling out risk-based explanations, and is not explained by payment-in-kind features. Our estimates show this premium significantly raises borrowing costs, reaching as high as 10.4% of firm earnings. These results suggest that BDCs pass through higher bank funding costs to borrowers, amplifying monetary policy transmission through the price channel. Notably, firms increase BDC credit utilization during

[5]For example, banks using internal estimates to set risk-based capital requirements may benefit from lower LGD on senior secured loans, provided the underlying collateral meets certain eligibility criteria; see Bank for International Settlements for further details.

tightening, suggesting that rising demand for private credit may be driving BDCs' increased reliance on bank financing.

Despite higher borrowing costs, firms increase their demand for BDC credit during monetary tightening for two reasons. First, firms facing constraints in obtaining additional bank credit, particularly when lending standards tighten, may turn to BDCs. Consistent with this, firms with high pre-existing bank loan utilization—those nearing their bank borrowing capacity—are significantly more reliant on BDC financing, highlighting BDCs' role in absorbing credit demand from bank-constrained borrowers, even at higher interest rates. Second, firms may prefer term loans over credit lines during tightening, as term loans offer greater certainty while credit lines can be reduced or revoked. Since BDCs offer a greater share of term loans than banks—who face balance sheet constraints due to capital requirements and regulatory scrutiny (Kashyap, Stein and Hanson, 2010), particularly in the term loan market (Irani, Iyer, Meisenzahl and Peydro, 2021)—BDCs become a natural alternative when banks tighten credit.[6]

Our final set of results examines how BDCs' reliance on bank financing influences their response to monetary tightening. Merging bank loan data with BDC deal-level investments and financing structures, we find that BDCs more reliant on bank credit exhibit stronger responses to tightening in both loan supply and pricing. During the 2022 tightening cycle, these BDCs expanded lending more aggressively and raised interest rates more than their less bank-reliant counterparts. This pattern supports a pass-through mechanism, where banks pass on higher funding costs to BDCs, who then adjust loan pricing while maintaining credit supply.

Taken together, our findings suggest that the expansion of bank lending to nonbank lenders mitigates the aggregate decline or deceleration in credit supply during monetary tightening but amplifies monetary policy transmission by raising borrowing costs. Our results underscore a key tradeoff in monetary policy transmission: while private credit dampens the quantity channel by maintaining lending, it amplifies the tightening of fi-

[6]Kashyap, Rajan and Stein (2002) show that deposit-taking banks have a comparative advantage in managing the liquidity risk of credit lines, unlike term loans. Consequently, nearly 60 % of bank loans are credit lines (Greenwald, Krainer and Paul, 2024). Additionally, banks earn fee-based income on undrawn credit line commitment and benefit from more lenient capital requirements on such exposures (Acharya, Jager and Steffen, 2023).

nancial conditions through the price channel.

Contribution to the Literature. Our paper contributes to research on the bank lending channel of monetary policy, which has primarily focused on how banks' direct lending to the corporate sector shapes policy transmission.[7] We expand this work by showing that banks also adjust lending to nonbank lenders—such as BDCs—which in turn supply credit to firms. Under this indirect credit supply mechanism, monetary policy affects aggregate credit not only through direct bank lending but also via shifts in credit allocation between banks and nonbanks.

Motivated by the post-GFC rise of nonbank lenders (Buchak, Matvos, Piskorski and Seru, 2018), recent work examines their role in monetary policy transmission (Elliott, Meisenzahl, Peydró and Turner, 2019; Xiao, 2020; Agarwal, Hu, Roman and Zheng, 2023; Elliott, Meisenzahl and Peydró, 2024; Cucic and Gorea, 2024). A key finding in this emerging literature is that nonbanks attenuate the impact of monetary tightening by providing more credit when banks pull back. We refine this view by highlighting a price-quantity tradeoff: although nonbanks dampen the quantity channel by maintaining lending, they amplify the price channel by passing on higher borrowing costs. Our paper is the first to study how credit flows from banks to nonbanks-and then to final borrowers-shape monetary policy transmission. We show that banks' financing of nonbanks matters, and that nonbanks dependent on bank funding exhibit stronger responses to monetary shocks.[8]

Finally, we contribute to the growing literature on private credit and direct lenders, focusing on BDCs, which are large players in this market. While prior work examines direct lenders' credit provision and its real effect, market discipline, lending terms, monitoring ability, and investment strategies (Davydiuk, Marchuk and Rosen, 2020a,b; Chernenko, Erel and Prilmeier, 2022; Jang, 2025; Block et al., 2024; Chernenko, Ialenti and Scharfstein,

[7] See, for example, Bernanke and Blinder (1988, 1992); Kashyap, Stein and Wilcox (1993); Jiménez, Ongena, Peydró and Saurina (2014); Bernanke and Gertler (1995); Kashyap and Stein (2000); Jiménez, Ongena, Peydró and Saurina (2012); Becker and Ivashina (2014); Drechsler, Savov and Schnabl (2017).

[8] Focusing on the mortgage market, Jiang (2023); Jiang, Matvos, Piskorski and Seru (2023); Agarwal et al. (2023) use shadow bank "call reports" and find that nonbanks operating in this sector primarily rely on short-term debt. Several recent studies also document the rise of bank lending to nonbank intermediaries like us (Acharya, Gopal, Jager and Steffen, 2024a; Gopal and Schnabl, 2022; Jiang, 2023; Javadekar and Bhardwaj, 2024; Acharya, Cetorelli and Tuckman, 2024b), but they do not examine the implications for monetary policy transmission.

2024; Haque, Mayer and Stefanescu, 2024; Davydiuk, Erel, Jiang and Marchuk, 2024), less is known about how BDCs finance their lending, especially during tightening cycles. We address this gap by showing that bank credit lines are central to BDCs' funding, and that BDCs actively renegotiate with banks to expand credit line limits in times of monetary tightening, reinforcing their role in monetary transmission. Related to our paper, Chernenko et al. (2024) argue that banks prefer lending to BDCs instead of direct middle-market lending because loans to BDCs are over-collateralized and thus require lower regulatory capital. We extend this view by showing that banks find lending to direct lenders particularly attractive during monetary tightening, as they can pass on interest rate increases more to BDCs than to non-BDC borrowers. This practice not only increases profitability but also benefits from lower loss-given-default rates.

2 Data and Empirical Facts

We primarily use the Federal Reserve's administrative matched bank–firm loan-level dataset for bank loan information and Refinitiv's BDC Collateral dataset for BDC investments. These datasets allow us to comprehensively track bank lending to both corporate borrowers and nonbank lenders, as well as the subsequent credit allocation by BDCs to firms. All variables are defined in Appendix A.1.

2.1 Data Sources

Matched Bank-Firm Loan Data from Federal Reserve's Y-14. Our primary source is the Federal Reserve's FR Y-14Q H.1 schedule on commercial loans (commonly referred to as the Y-14 data).[9] This dataset covers detailed information on the universe of bilateral and syndicated loan facilities over \$1 million in committed amounts held by Bank Holding Companies (BHCs) that are subject to the Federal Reserve's Stress Tests.[10] These report-

[9] For details on variables contained in schedule H.1 and how banks are required to report information to the Federal Reserve, see the Table beginning in page 170 in the publicly available reporting form.

[10] A loan facility is a lending arrangement between a bank and a borrower, which may include multiple loans of different types (e.g., credit lines or term loans). Banks classify the facility type according to the loan type with the majority of the total commitment amount (Greenwald et al., 2024).

ing banks hold over 85% of total assets in the U.S. banking sector (Caglio, Darst and Kalemli-Özcan, 2021) and account for roughly 70–75% of all Commercial & Industrial (C&I) lending (Bidder, Krainer and Shapiro, 2021; Minoiu, Zarutskie and Zlate, 2021).

The Y-14 data offers a granular view of loan contracting across a wide spectrum of firms on a quarterly basis. Besides committed and utilized loan amounts for each lending facility, the dataset captures key loan-level attributes, such as interest rates, spreads, maturity, priority in bankruptcy, collateral, and ex-ante estimates of loss given default (LGD), loan-type (e.g., credit line or term loan). The origination date allows us to separate new loans from existing ones each quarter. Banks also report financial, accounting, and balance sheet information for their borrowers over time annually. Additionally, we observe borrower-level risk measures, including internal credit ratings and time-varying default probabilities, which enable us to control for borrower risk and rule out risk-based explanations for differences in interest rates between loans to BDCs and non-BDCs.[11]

Our analysis primarily relies on quarterly loan-level data and annual borrower-level financials.[12] Although reporting began in 2011Q3, we start our sample in 2012Q3 when coverage of banks improved significantly, and also to allow for a phase-in period for the structure of the collection and variables to stabilize. Appendix A.2 details our data cleaning and filtration procedures.

BDC Data from BDC Collateral. We use Refinitiv (LSEG)'s BDC Collateral dataset, which compiles mandatory SEC filings into a quarterly panel, to collect data on all public and private BDCs and their portfolio investments from 2012Q3 to 2023Q4. The dataset covers 190 unique BDCs, ensuring broad representation of the sector. Because BDCs must report their holdings to the SEC, the dataset is free from selection bias due to non-random missing data. The dataset also assembles BDCs' financial data from their SEC filings, including for private BDCs not covered by Compustat.

[11]Prior studies have shown that banks' internal credit assessments are highly informative of borrower risk (Weitzner and Beyhaghi, 2022; Beyhaghi, Howes and Weitzner, 2024; Lee, Li, Meisenzahl and Sicilian, 2019) and their estimates of loss given default and probability of default can predict a borrower's future equity returns, bond returns, and earnings surprises (Beyhaghi et al., 2024).

[12]Borrower-level financials are available for around 60% of firms in the dataset, with reporting more frequent among larger firms.

The dataset provides detailed loan-level information, including the borrower's name, industry, and contractual terms such as par amount, interest rates, maturity, seniority, and loan type.[13] BDC reports classify three types of loan seniority—first lien, second lien, and subordinated—and provide performance metrics, including fair value and non-accrual status (i.e., whether a loan is nonperforming). We use our comprehensive list of BDCs to hand-collect their unique Taxpayer Identification Number (TIN) from SEC filings. Appendix A.3 presents our data cleaning and filtration procedures.

Representativeness of BDC Collateral. To assess whether BDC borrowers in BDC Collateral data are representative of the broader private credit market, we compare key variables across multiple private credit datasets. First, Jang (2025) utilizes a proprietary database covering a significant share of loans extended by both BDCs and private credit funds and finds that the database is representative of the private credit borrowers in PitchBook. As shown in Appendix A.3, our sample exhibits no significant differences from Jang (2025)'s data in terms of the prevalence of first-lien loans or average loan interest rates.[14] Second, when comparing the distribution of loan amounts and spreads, we find that our sample closely aligns with other studies, including Davydiuk et al. (2020a), who uses hand-collected data on BDCs, and Haque et al. (2024), who uses Pitchbook data. Overall, we find no evidence that borrowers in BDC Collateral are systematically different—particularly in terms of credit risk—from those studied in other private credit research. Given their similar portfolio holdings, we believe our conclusions from examining BDC data are highly likely to apply to other types of private credit funds.

Matching BDCs to Y-14. We match individual BDCs that borrow directly from banks to the Y-14 data primarily using their TIN. This method identifies 133 BDCs, with an

[13] While BDCs invest in debt, equity, and structured products, the majority of their portfolios consist of debt investments. The dataset includes three interest rate measures: all-in yield, cash spread over the base rate, and Payment-in-Kind (PIK) spread. PIK interest accrues to the loan principal instead of being paid in cash. Unlike the Y-14 data, however, BDC Collateral does not contain financial information on BDCs' borrowers (investees), as BDCs are not required by the SEC to disclose such details.

[14] Loan type and interest rates are the only variables directly comparable across both datasets. Since both rely on investor holdings data, they provide only partial coverage of loan issuance dates, limiting our ability to measure loan maturity accurately.

additional 9 matched using the string-matching algorithm from Cohen, Dice, Friedrichs, Gupta, Hayes, Kitschelt, Lee, Marsh, Mislang, Shaton et al. (2021), bringing the total to 142 BDCs as borrowers from banks in the Y-14 data.[15] These include 56 public BDCs (80% of all public BDCs) and 86 private BDCs (74% of all private BDCs), covering approximately 75% of all BDCs in our sample and 90% in dollar-weighted terms as noted in Section 2.2.[16]

Matching BDC Portfolio Companies with Y-14. To obtain the set of overlapping borrowers—firms that hold both bank loans and BDC credit—we match BDC portfolio companies to the borrowers in Y-14 data each quarter using a string-matching algorithm based on borrower name and industry, following Cohen et al. (2021). Each match is then manually verified for accuracy.

Monetary Policy Measures. Given our primary focus on the 2022 monetary tightening due to its unprecedented speed, magnitude of rate hikes, and the accompanying slowdown in bank credit growth, we measure the stance of U.S. monetary policy mainly using (1) a dummy variable for the 2022 tightening cycle (2022Q1–2023Q4)—although rate hikes ended in July 2023, we include 2023Q4 as rates remained elevated—and (2) changes in the effective Federal Funds rate.

Since the Federal Funds rate is endogenous to broader economic conditions affecting both credit demand and supply, we also incorporate monetary policy shocks to assess robustness. Specifically, we use the shocks identified by Jarociński and Karadi (2020), which isolate unexpected monetary policy shifts using high-frequency changes in short-term interest rate derivatives around FOMC announcements. Additionally, we employ an updated version of the Bauer and Swanson (2023) measure, which similarly captures

[15]The matching algorithm, known as "Fedmatch," uses a two-stage matching method that pairs traditional string matching techniques with probabilistic record linkage methods. For details, see Cohen, Dice, Friedrichs, Gupta, Hayes, Kitschelt, Lee, Marsh, Mislang, Shaton et al. (2021). An R package implementing this method is available on Github.

[16]Our detailed examination of the names of nonbank financial intermediaries borrowing from the Y-14 banks suggests that the unmatched 25 percent of BDCs did not have outstanding commitments from Y-14 banks during our sample period. Manual verification of SEC credit agreements confirms that nearly three-quarters of these BDCs have outstanding loans from non-Y-14 banks (e.g., ING Capital or Natixis), while some others appear to strategically opt to operate without bank debt, as indicated by their names such as "XXXXXXX Unlevered Corp BDC," where we have redacted the identifying name.

unexpected policy changes during FOMC meetings.

2.2 Empirical Facts

Bank Lending to BDCs. Bank lending to BDCs saw steady growth throughout most of our sample period (Figure 1), with a sharp increase starting in 2021 that continued through the 2022–2023 monetary tightening. In the past three years, total bank loan commitments more than doubled, reaching over $60 billion. Table 1 reports loan-level summary statistics for key variables in our analysis, distinguishing between loans to BDCs (Panel A) and to non-BDCs (Panel B). Below, we highlight some key characteristics of bank loans to BDCs.

Bank loans to BDCs are significantly larger than those to non-BDC borrowers. The average committed loan to a BDC is approximately $90 million, while the median is $50 million—about 7 times and 14 times the respective sizes of loans to non-BDC borrowers. A similar pattern holds for the utilized loan amount. While interest rates are comparable across borrowers in the cross section, an important nuance emerges when examining the time series. Figure 2 plots the weighted average interest rates of bank loans to BDCs and non-BDCs, where the weights are the utilized loan amounts. Notably, BDC loans generally carry higher rates during periods of monetary tightening relative to loans to non-BDCs. Finally, bank loans to BDCs tend to have shorter maturities, reflecting their heavy reliance on credit lines, as discussed next.

More than 70% of bank loans to BDCs—and nearly 90% in dollar-weighted terms, as shown in Figure 1—are credit lines.[17] These fractions are significantly higher than loans to non-BDCs. Credit lines allow borrowers to draw funds up to a precommitted amount at a predetermined spread. Unused credit line capacity helps borrowers sidestep adverse changes in aggregate lending conditions. Notably, BDCs exhibit higher utilization rates of credit lines than non-BDCs.

Bank loans to BDCs generally offer greater protection to creditors. Examining banks' own ex-ante estimate of loss given default (LGD), we find that the average LGD for BDC

[17] While Acharya et al. (2024a) also document that banks provide credit lines to nonbanks, their focus is on REITS and banks' risk exposure to the CRE market.

loans is about 10 percent lower than for non-BDC loans. A likely explanation is that BDC loans are more frequently collateralized, with banks holding first-lien, senior secured positions in bankruptcy, as shown in Table 1.

BDC Investments and Financing. Our BDC sample covers all BDCs, which must file SEC 10-K/10-Q reports detailing their portfolio holdings. As of 2023Q4, BDCs hold $318 billion in total assets and $301 billion in total investments. BDCs primarily lend to middle-market firms, which account for a third of private-sector GDP.[18] Table 2 shows summary statistics for BDC loan portfolios. The average loan size is $11.31 million, with a maturity of about four years. BDC loans carry high interest rates, with an average all-in-yield of 9.38% and an interest spread of 7.19%, reflecting their focus on riskier borrowers while also offering payment flexibility and relationship lending benefits (Block et al., 2024; Jang, 2025).[19]

While BDCs finance their debt through both bonds and loans, their reliance on bank funding has grown significantly.[20] Among the 190 BDCs in our sample, 142 borrowed from banks during our sample period and thus appear in the Y-14 data. These bank-reliant BDCs play a dominant role in the credit market, providing funding to around 11,500 firms—most of which are private—and consistently accounting for around 90% of total BDC lending (Appendix Figure A.3). The average ratio of bank loan commitments (from Y-14) to BDC assets has roughly doubled over time, with notable growth following the relaxation of BDC regulatory leverage limits (Balloch and Gonzalez-Uribe, 2021) and during the 2022 monetary tightening cycle (upper panel, Figure 3). Interest expenses have also become increasingly tied to bank loans, with a sharp spike in 2022 during monetary tightening (lower panel, Figure 3).

Smaller BDCs, with limited access to bond markets, rely even more on bank funding

[18] According to the National Center for the Middle Market, middle-market firms are those with annual sales between $10 million and $1 billion. A survey of C-suite executives from these firms estimates that nearly 200,000 middle-market businesses in the U.S. account for one-third of private sector GDP; see here.

[19] The interest rate spread includes a 0.51% payment-in-kind (PIK) spread. While PIK is not very common in normal times, its prevalence tends to surge during periods of market distress, such as COVID-19 and the 2022 monetary tightening (Figure A.1).

[20] The average BDC leverage (Debt/Asset) is 0.4 in our sample. As shown in Figure A.2, leverage has steadily increased, partly driven by the Small Business Credit Availability Act (SBCAA) passed in March 2018.

(Figure A.4). While our sample includes both public and private BDCs, recent growth has been driven primarily by private BDCs (Figure A.5). This expansion aligns with their increasing reliance on bank financing (Figures 1 and 3). The greater dependence of private BDCs on bank funding is consistent with them facing higher information asymmetry and thus requiring more informationally-sensitive loans from banks (Diamond and Dybvig, 1983; Diamond and Rajan, 2001).

Empirical Facts on Bank Credit over the 2022 Tightening Cycle. By classifying Y-14 loan-level data by borrowers into BDCs and non-BDC loans, we uncover key aggregate patterns. For each borrower group and quarter, we compute the quarterly growth of total loan commitments, average credit-line utilization rate, and average loan rates. Figure 4 (and Appendix Table A.1) reports the mean values for both the 2022 monetary tightening cycle (2022Q1–2023Q4) and non-tightening periods (when the Fed Funds rate did not increase), revealing two novel findings.

First, while credit availability–measured by loan commitments–for non-BDC borrowers slowed from 3.4% to 2.5% in the 2022 monetary tightening cycle, bank credit to BDCs accelerated from 6.3% to 6.8%, suggesting that banks reallocated credit toward BDCs. Similarly, utilization rates declined for non-BDCs but remained stable for BDCs. These patterns indicate that as credit conditions tighten, BDCs receive a greater share of bank lending and draw more heavily on their credit lines. Second, while interest rates for BDC and non-BDC loans were comparable before the tightening, rates on BDC loans rose more sharply during the 2022 tightening cycle—to 6.1% versus 5.4% for non-BDC borrowers—suggesting banks charge a premium to these nonbank lenders during monetary contractions. Since BDCs pass on their higher funding costs to their own borrowers, this premium amplifies monetary-policy transmission by raising borrowing costs for firms—a mechanism we test more formally in Section 4.

3 Results on Bank Lending to BDCs

This section presents our regression results on the first part of the intermediation chain—banks lending to nonbank direct lenders. Using granular supervisory bank loan data, we estimate how bank lending to BDC borrowers responded differently from lending to other borrowers during the 2022 monetary tightening cycle. Our goal is to examine both the quantity and pricing of bank loans to BDCs relative to other borrowers and to uncover the underlying mechanisms driving these differences.

3.1 Regression Framework

Since each borrower can have multiple outstanding loans from the same bank, we aggregate the quarterly loan-level data into a bank-borrower-quarter panel to capture the total credit provision for each borrower-bank pair. Loan amounts are measured as the sum of total committed or utilized amounts across lending facilities, while borrowing costs are captured using interest rates weighted by utilized amounts.

We estimate the following baseline regression model:

$$Y_{i,b,t} = \alpha + \beta_1(BDC_i \times MP_t) + \beta_2 BDC_i + X_{i,t-1} + FE_{b,t} + \epsilon_{i,b,t}, \tag{1}$$

where $Y_{i,b,t}$ represents borrower (i)-bank (b)-quarter (t) level outcomes, including: (i) quarterly growth rate of loan commitments, (ii) loan utilization rate for credit lines, (iii) interest rate, weighted by loan utilization, and (iv) credit risk measures, such as seniority in bankruptcy, collateralization, loss given default, and probability of default.

MP_t captures the stance of contractionary monetary policy, measured by a dummy for the 2022 tightening cycle ($Tightening_t$) and changes in the effective Fed Funds rate (ΔFF_t). BDC_i is a dummy variable indicating whether the borrower is a BDC. We include lagged borrower-level control variables ($X_{i,t-1}$) to account for observed heterogeneity and a vector of fixed effects ($FE_{b,t}$) to account for unobserved heterogeneity.

Our primary coefficient of interest, β_1, captures the differential response of lending to BDC borrowers during monetary tightening, whether in terms of loan quantity or pricing.

For example, if bank lending to BDCs expands during monetary tightening—potentially mitigating a broader credit contraction or slowdown—we expect β_1 to be positive.

Borrower-Level Controls. To account for observable differences between borrowers, we include a set of lagged borrower-level characteristics ($X_{i,t-1}$) to capture default risk, leverage, and bank loan usage. These variables are derived from the Y-14 data and include bank-estimated probability of default, expected loss given default, total bank debt, the share of term loans in total bank debt, and the share of credit lines in total bank debt. These variables control for key differences between BDCs and other borrowers such as leverage, firm size, debt structure etc. All control variables enter the regression with a one-period lag.

Fixed Effects. To compare loans with nearly identical levels of credit risk, we leverage bank-internal credit ratings reported in the Y-14 data, which we refer to as *credit rating*. These ratings are highly granular, borrower-specific, and bank-dependent, as they are derived from individual banks' internal risk assessment models.[21] As these ratings generally reflect borrower characteristics such as leverage or firm size and are updated over time—where poor loan performance typically results in a downgrade—recent studies have shown that they are highly informative about borrower characteristics, particularly credit risk and loan outcomes (Weitzner and Howes, 2023; Beyhaghi et al., 2024; Haque, Mayer and Wang, 2023; Claessens, Ongena and Wang, 2024). Indeed, Lee et al. (2019) document that banks' internal credit ratings are highly correlated with credit spreads.

Our specification includes *bank*×*credit rating*×*year-quarter* fixed effects, ensuring that we compare loans made by the same bank, within the same quarter, to BDC and non-BDC borrowers with the same internal credit rating. By construction, these fixed effects absorb the direct effect of monetary policy series (MP_t) and account for time-varying heterogeneity across lenders, such as differences in banks' internal risk assessment models or capital ratios, which can influence lending decisions (Irani et al., 2021). We double cluster standard errors at *bank* × *borrower* and *YearQtr* levels, and the sample period spans 2012Q3–2023Q4.

[21] Banks in our sample typically have 10 to 15 rating buckets, though some employ even more detailed credit rating classifications.

3.2 Baseline Results

Our results, presented in Table 3, show that banks significantly increased lending to BDC borrowers and charged them higher rates relative to non-BDC borrowers during the 2022 monetary tightening cycle. Column (1) shows that loan commitments to BDCs grew by 1.1 percentage points more than those to other borrowers during the tightening cycle, while no such differences were observed in non-tightening periods. This effect is economically significant, as its magnitude is comparable to the sample mean of loan commitment growth for BDCs in Table 1.

Since most bank loans to BDCs are credit lines, we next examine utilization rates. Column (2) shows that BDCs utilized credit lines 18.6(=14.2+4.4) percentage points more than non-BDC borrowers during the tightening cycle, a significant increase from the 4.4 percentage point difference observed in normal periods. This effect is economically large, given that the average credit line utilization rate is around 50%.

Column (3) shows that banks charged BDC borrowers higher interest rates, with this premium primarily driven by the 2022 tightening. The interest rate spread between BDC and non-BDC borrowers widened by 1.1(=0.9+0.2) percentage points, an economically meaningful increase, representing 25% of the unconditional mean of bank loan rates to BDCs (Table 1). This rate premium results in an additional annual loan expense of $0.3 billion for BDC borrowers, accounting for 15% of their total bank loan expenses. [22] By incorporating lagged borrower credit risk measures (probability of default, expected LGD) as controls and granular bank-internal credit ratings as fixed effects, our strategy ensures a comparison of loans with nearly identical levels of credit risk, thus ruling out credit risk differences as an explanation for the rate premium.

Columns (4)–(6) of Table 3 confirm that our findings hold when using changes in the Fed Funds rate (ΔFF_t) as an alternative policy measure. Since the Fed Funds rate reflects broader economic conditions affecting credit demand and supply, we conduct robustness tests using monetary policy shocks from Jarociński and Karadi (2020) and Bauer and Swanson (2023) in Section 6. Taken together, these findings indicate that banks re-

[22] By 2023Q4, total utilized bank loans by BDCs reached $27.24 billion, with total bank loan expenses of $2.05 billion.

allocated credit toward BDCs during monetary tightening, indirectly supporting credit supply while raising borrowing costs.

3.3 The Renegotiation Channel

Credit provision through credit lines involves active decision-making and renegotiation, with banks setting credit limits and borrowers deciding how much to draw. Leveraging granular loan-level data, we gain deeper insight into how banks shift credit to BDCs and whether this expansion is driven by renegotiation of existing credit lines or the origination of new loans.

In Panel A of Table 4, we separately examine credit lines by three groups: pre-existing credit lines (Column 1), pre-existing credit lines with credit limit expansions (Column 2), and newly originated credit lines (Column 3). Our findings indicate that BDC borrowers predominantly obtain additional credit through renegotiation. Column (2) shows that loan commitments to BDCs grew by 3.6(=4.7-1.1) percentage points more than those to other borrowers when restricting to pre-existing credit lines with positive commitment changes. The results remain robust when using changes in the Fed Funds rate as an alternative measure.[23] These patterns align with prior research on loan contracting, showing that bank loans are frequently renegotiated as borrowers seek to adjust loan terms in response to updated information on credit quality and investment opportunities (Roberts and Sufi, 2009; Denis and Wang, 2014).

We then examine how BDC borrowers utilize credit during monetary tightening, aiming to identify which loan types saw the greatest increase in drawdowns. Specifically, we examine the growth rate of utilized credit line amounts for all credit lines (Column 1), for pre-existing credit lines (Column 2), and for pre-existing credit lines with credit limit expansions (Column 3). As shown in Panel B of Table 4, BDC borrowers significantly increased credit line drawdowns during monetary tightening, with a substantial portion of the increase coming from credit lines that underwent limit expansions (Column 3).

Overall, Table 4 suggests that BDC borrowers primarily obtain additional credit through

[23]Column (6) shows that as the Fed Funds rate rises, new loan origination to BDCs declines relative to other borrowers, reinforcing the role of credit line expansions in credit allocation.

renegotiation of existing credit lines, reflecting a coordinated interplay between banks and borrowers. BDC borrowers draw more from existing credit lines, while banks respond by increasing credit limits on the most utilized loans. Combined with the simultaneous rise in both the quantity and price of bank credit for BDC borrowers, these results suggest that this trend is largely driven by heightened demand from BDCs seeking profitable investment opportunities.

3.4 Why Do Banks Prefer Lending to BDCs over Lending to Firms?

The simultaneous increase in both the quantity and price of bank credit for BDC borrowers suggests heightened demand for credit, raising two key questions: Why do banks prefer lending to BDCs over directly lending to firms? And does this credit expansion to BDCs, coupled with higher loan rates, reflect increased risk-taking by banks during monetary tightening? Our analysis suggests otherwise. We find that banks' increased lending to BDCs is primarily driven by profitability rather than risk-taking.

First, loans to BDCs provide attractive returns relative to their credit rating without exposing banks to additional credit risk. While these loans carry higher interest rates (Table 3), banks appear to face lower credit risk. Table 5 reveals that, during monetary tightening, loans to BDCs are more likely to be first-lien senior secured and collateralized, granting banks priority over borrower assets in the event of default. Moreover, these loans exhibit significantly lower loss given default (LGD) with no statistically significant difference in ex-ante default probabilities compared with loans to other borrowers. These patterns may indicate that banks have market power in the funding market for BDCs, similar to what Jiang (2023) find in mortgage markets.

Second, banks benefit from lower funding costs due to favorable capital treatment for senior collateralized credit facilities extended to BDCs, an effect that is more pronounced during monetary tightening. As shown in Table 5, loans to BDCs are more likely to be secured by collateral, especially during the 2022 tightening cycle. While banks are generally not capital-constrained, issuing collateral-backed loans provides a regulatory advantage, as such loans carry lower capital requirements, aligning with the arguments in Chernenko et al. (2024). This feature further enhances the attractiveness of lending to BDCs over direct corporate lending.

4 BDC Lending during Monetary Tightening

Having established that banks charge BDCs higher interest rates relative to other borrowers during monetary tightening, we now turn to the second part of the intermediation chain—BDC lending to firms. We aim to determine whether BDCs, in turn, charge their borrowers higher interest rates than banks and whether this effect intensifies during monetary tightening. If BDC funding costs from banks rise under contractionary policy, we expect to observe a corresponding increase in BDC lending rates.

4.1 Khwaja-Mian Regressions on Overlapping Borrowers

A key challenge in identifying this pass-through effect is that BDCs may select riskier borrowers under-served by banks (Block et al., 2024), making it difficult to isolate whether higher BDC lending rates stem from elevated funding costs or greater borrower risk. For example, Elliott et al. (2019) show that nonbanks expand credit supply during monetary contractions by increasing risk-taking, lending to borrowers with higher default risk.

To address this concern, we merge the Y-14 data with BDC Collateral investment data to identify firms that hold both bank loan commitments and BDCs private credit—a group we term "Overlapping Borrowers"—and employ a regression framework similar to Khwaja and Mian (2008) or Chodorow-Reich (2014). We document a significant and growing number of overlapping borrowers, consistent with Haque et al. (2024). Across our sample, we identify about 4,800 overlapping borrowers, with their numbers increasing substantially in recent years, particularly during the recent monetary tightening cycle (Figure A.6). These borrowers primarily rely on bank credit lines but also obtain some term loans (Figure A.7). Summary statistics in Table A.2 show that overlapping borrowers tend to be larger, more leveraged, have lower interest coverage ratios, and possess fewer tangible or collateralizable assets than non-overlapping borrowers.

To test whether BDC-originated loans carry higher interest rates and amounts than bank loans—even within the same borrower, quarter, and loan type—we construct a loan-time panel dataset that stacks bank- and BDC-originated loans to overlapping borrowers. We estimate the following regression:

$$Y_{l,t} = \alpha + \beta_1(BDC_l \times MP_t) + \beta_2 BDC_l + X_{l,t} + FE_{i,t,z} + \epsilon_{l,t} \tag{2}$$

where $Y_{l,t}$ represents loan (l)-quarter(t) level outcomes, including interest rate, loan amount, and loan type for a given loan l of type z at year-quarter t extended to borrower i. Loan type z can be a credit line, term loan, or other forms of lending. BDC_l is a dummy variable equal 1 for BDC loans and 0 for bank loans. MP_t is a time-series variable capturing the stance of contractionary monetary policy.

Crucially, we include borrower × time × loan type fixed effects ($FE_{i,t,z}$) to control for time-varying borrower characteristics—such as credit demand or private equity backing—that may influence credit spreads or loan amounts, as well as systematic differences across loan types. This specification ensures that BDC and bank loans are compared within the same borrower, quarter, and loan type, isolating differences in pricing or loan amounts from borrower risk and demand variations. Additional loan-level controls in $X_{l,t}$ include indicators for non-accruing loans, maturity and loan amounts (when the dependent variable is interest rate, and vice versa). Standard errors are double-clustered at the borrower and year-quarter level.

Panel A of Table 6 presents the results. Column (1) confirms that BDC-provided loans carry significantly higher interest rates than bank loans. More importantly, the coefficient on $BDC \times Tightening$ is positive and statistically significant at 1% level, indicating that BDC lending rates rise even more relative to bank rates during monetary tightening. Given our strict fixed effects, this result cannot be attributed to borrower risk differences or loan type variations (e.g., credit lines vs. term loans).

To address alternative explanations, we introduce additional controls. In Column (2), we control for loan seniority, adding fixed effects for first-lien senior secured, second-lien senior secured, and junior/unsecured debt to capture variation in debt seniority that could affect interest rates. Column (3) controls for PIK spreads, a feature of some private credit facilities that allows borrowers to defer interest payments until maturity at the cost of higher interest rates.[24] Since BDCs' tendency to offer PIK options may rise during monetary tightening (Figure A.1), we also interact $Log\ (1+\ PIK\ Spread)$ with the tightening dummy. Despite these additional controls, the coefficient on $BDC \times Tightening$ remains positive, stable, and significant. Notably, the negative coefficient on $Log(1+PIKSpread) \times Tightening$ in Column (4) suggests that this effect is not driven by an increase in PIK loans. Overall, our results suggest that BDC lending rates increase more than bank rates during monetary tightening, independent of credit risk, loan seniority, and PIK prevalence.

In Columns (5) and (6), we turn to examining utilized loan amounts. We use utilized amounts rather than commitments because BDC collateral reports only utilized amounts, while Y-14 provides both. We find that firms increase their utilization of BDC loans relative to bank loans during tightening. This finding suggests that rising demand for private credit may be prompting BDCs to expand their loan supply, aligning with our earlier findings that banks shift lending toward private credit funds during monetary contractions.

Economic Significance The point estimates from Tables 3 and 6 enable back-of-the-envelope calculations to assess the magnitude of the rate amplification along the bank-BDC and BDC-firm segments of the intermediation chain. We approach this in two ways: first, by comparing our estimates to prior research on monetary policy transmission, and second, by quantifying the implied increase in firm-level interest expenses.

As noted earlier in Section 3.2, banks charge BDCs an additional 1.1 percentage points in interest during tightening. In turn, BDCs pass on a 1.47(=0.521+0.949) percentage point premium to firms (Table 6, Column 1). These magnitudes are sizable relative to prior studies. For instance, Erel, Liebersohn, Yannelis and Earnest (2023) document that online (fintech) banks charged borrowers 0.4 to 1.5 percentage points more than traditional banks during the 2022 tightening cycle, depending on the loan type.

We next quantify the additional interest expense for overlapping borrowers. As re-

[24]See, for example, this Fitch Ratings article on the increasing use of PIK features in private credit.

ported in Appendix Table A.2 (Panel A), the median firm in our sample holds $254 million in debt and reports $36 million in EBITDA. Given that BDC and bank loans are roughly equal in size, we assume that private credit comprises 50% of total debt for the median overlapping borrower. Under this assumption, the additional interest expense from BDC credit during tightening amounts to 5.1% of firm earnings. The cost burden is even greater for more constrained borrowers with limited bank credit access, as the total interest rate premium approaches 2 percentage points (Column (1) in Panel B of Table 6), further amplifying financial strain. Finally, if we extend our estimates to non-overlapping borrowers that rely exclusively on private credit, the implied additional interest expense during tightening rises to $10.4\% = \left((254 \text{ x } 0.0147)/36\right)$ of firm earnings.[25]

4.2 Why Do Borrowers Prefer Private Credit over Bank Credit?

The increased utilization of BDC loans at higher interest rates compared with bank credit during monetary tightening suggests a rising demand for BDC financing. But why do borrowers opt for BDC loans despite their higher costs? We provide evidence for two key explanations.

First, some borrowers turn to BDCs because they face constraints in securing additional bank credit, particularly when lending standards tighten.[26] To test this, we re-estimate Eq. (2) by dividing overlapping borrowers into those likely constrained in bank lending and those that are not. A borrower-quarter is classified as *bank loan constrained* if the lagged utilization rate of bank loans exceeds the 75th percentile of the sample distribution, indicating that the borrower has nearly exhausted its bank borrowing capacity. These borrowers are more likely to be constrained in accessing further bank credit and may be forced to seek alternative financing at higher costs. The results, presented in Panel B of Table 6, show that our results are more pronounced for bank loan-constrained borrowers, consistent with the bank lending constraints mechanism.

[25] This extension is reasonable, given the similarity between loans to overlapping and non-overlapping borrowers. Specifically, the mean loan amount is $15 million (interest rate: 9.1%) for overlapping borrowers and $12.4 million (interest rate: 9.6%) for non-overlapping borrowers.

[26] According to the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS), bank lending standards began tightening in 2022Q3 and, by 2023, had reached levels last seen during the Global Financial Crisis and the COVID-19 pandemic.

Second, firms may increasingly favor permanent financing, such as term loans, over credit lines during tightening, making BDCs a natural alternative as they provide a greater share of term loans than banks. Bank loans are primarily credit lines, as rising capital requirements have constrained banks' balance sheet capacity, particularly for term loans, which are more capital-intensive (Kashyap et al., 2010; Irani et al., 2021). Credit lines are more affordable for banks to offer due to synergies between deposit-taking and credit line lending (Kashyap et al., 2002; Pennacchi, 2006).[27] Furthermore, as the majority of credit lines remain undrawn, banks benefit from lower capital requirements on credit lines while earning fee-based income on undrawn facilities. When monetary policy tightens, firms may shift towards term loans for greater certainty, as credit lines can be reduced or revoked if a borrower's financial health deteriorates or if the bank faces funding pressures (Sufi, 2009; Chodorow-Reich and Falato, 2022), particularly given that credit lines are more covenant-heavy (Berlin, Nini and G. Yu, 2020). By contrast, term loans are fully disbursed at origination, reducing lender discretion and providing stability to borrowers in uncertain conditions. Consistent with this mechanism, we find in Columns (7)–(8) of Panel A in Table 6 that BDC loans have a significantly higher share of term loans, particularly during the 2022 monetary tightening.

Additional to the above two reasons, BDC loans may also offer other benefits that are difficult to quantify, such as faster loan approval, customized covenant structures tailored to borrowers' needs, greater flexibility in renegotiation, and more stable relationships (Block et al., 2024; Jang, 2025; Degerli and Monin, 2024).

5 The Intermediation Chain

This section examines how banks' financing of BDCs influences monetary policy transmission along the intermediation chain. Specifically, we test whether BDCs' credit supply responses to monetary tightening depend on their reliance on bank funding. If monetary policy transmits from banks to BDCs and subsequently to firms along the intermediation

[27] As argued by Pennacchi (2006), during market stress, investors view banks as safe havens due to deposit insurance and other backstops, leading to increased deposits just as borrowers draw from their commitments.

chain, we expect BDCs that depend more heavily on bank financing to exhibit stronger responses to tighter monetary policy. During the 2022 monetary tightening cycle, we anticipate that these BDCs increase their loan supply to firms while simultaneously raising borrowing costs, relative to less bank-reliant BDCs.

To test this, we leverage unique features of our dataset that merges granular data on bank loans to BDCs with deal-level investment records and BDCs financials. This integrated dataset enables us to trace the full intermediation chain, providing an ideal setting to examine how monetary policy propagates through banks' financing of BDCs.

We measure a BDC's reliance on bank financing using $BankLoanExpense_{i,t}$, the share of interest payments on bank loan over total interest expenses for BDC i in quarter t. An increasing share of BDCs' interest payments are attributable to outstanding bank loans over time (Figure 3), and higher share reflects greater reliance on bank credit in the cross-section. We then estimate the following model:

$$Y_{i,j,t} = \alpha + \beta_1(BankLoanExpense_{i,t} \times MP_t) + \beta_2 BankLoanExpense_{i,t} + X_{i,j,t} + FE_{b,t} + \epsilon_{i,j,t}, \quad (3)$$

where $Y_{i,j,t}$ represents BDC (i)-loan (j)-quarter (t) level outcomes, including loan amount (investment by BDC) and interest rate. MP_t is a time-series variable capturing the stance of contractionary monetary policy. To account for potential confounding factors, we include a set of controls, $X_{i,j,t}$, including total BDC assets (to isolate credit supply effects from portfolio expansion), loan maturity, and non-accrual status (to account for credit risk). Section 6 considers alternative BDC-level controls. To address unobservable heterogeneity, we include BDC fixed effects to control for unobservable, BDC-specific preferences for certain borrower types; year-quarter fixed effects to absorb time-varying macroeconomic conditions that could impact the amount and cost of BDC lending; and loan-type fixed effects to account for risk variations across loan structures. Our coefficient of interest is β_1, the coefficient of the interaction term $BankLoanExpense_{i,t} \times MP_t$, which measures whether BDCs more reliant on bank funding exhibit amplified lending responses to monetary policy changes.

Table 7 presents the results. Columns (1)–(2) examine loan amount, while columns

(3)–(4) examine interest rate. The estimate for the interaction term $BankLoanExpense_{i,t} \times MP_t$ is consistently positive and statistically significant at the 1% level across all columns.[28] These results suggest that higher reliance on bank loans are associated with greater loan amount and higher interest rates during the 2022 monetary tightening.

The magnitude of the effect is economically significant. A BDC with a one-standard-deviation higher *BankLoanExpense* (0.48) expands loan supply by 20.5% (0.48 × 0.428) and raises borrowing costs by 15 basis points (0.48 × 0.313) more than in non-tightening period. This pattern aligns with a pass-through mechanism: as banks' funding costs rise, they pass them to BDCs, who in turn reprice their loans to maintain margins while increasing lending where rates remain attractive.

One potential concern is that BDCs' reliance on bank financing may be endogenous to their characteristics, such as access to alternative funding sources or investment strategies. For instance, bank-dependent BDCs may cater to distinct borrower types or be influenced by banking relationships. While we cannot entirely rule out endogeneity, the persistence of BDCs' bank reliance over time suggests that these relationships are relatively stable and unlikely to be driven by short-term credit decisions. Additionally, reliance on bank funding at the intensive margin is likely shaped by market-wide conditions, particularly BDCs' ability to substitute between bonds and loans—a factor we control for using year-quarter fixed effects.

To further validate our findings, we conduct robustness checks using alternative measures of BDCs' bank reliance (Section 6), as well as additional tests incorporating monetary policy shocks and alternative control variables. Across all specifications, our results remain consistent.

Taken together, our evidence suggests that BDC funding structure plays a critical role in monetary policy transmission. During the 2022 tightening, BDCs more reliant on bank financing responded more sharply to policy changes—expanding lending more than their less bank-reliant counterparts while simultaneously charging higher interest rates. Our

[28] Across all specifications, the coefficient on *BankLoanExpense* is negative and statistically significant, suggesting that, under normal conditions (i.e., with no hikes in the Fed fund rate), greater reliance on bank debt is associated with smaller loan amounts (Columns 1–3) and lower interest rates (Columns 4–6). This suggests that bank-dependent BDCs may be more conservative in lending or prefer stable, lower-risk pricing structures.

findings underscore the importance of nonbank lenders and their funding structures in shaping the transmission of monetary policy.

6 Robustness

This section presents a series of robustness tests to validate our findings and rule out alternative explanations.

Robustness with Monetary Policy Shocks In our baseline analysis, we measure the stance of U.S. monetary policy using a dummy variable for the 2022 tightening cycle (2022Q1–2023Q4) and changes in the effective Federal Funds rate. However, both measures are endogenous to broader economic conditions that influence credit demand and supply. To address this, we assess the robustness of our results using monetary policy shocks that isolate unexpected changes in policy.

Specifically, we incorporate the high-frequency shocks identified by Jarociński and Karadi (2020), which use short-term interest rate derivative movements around FOMC announcements to isolate unanticipated monetary policy shifts. Additionally, we employ an updated version of the Bauer and Swanson (2023) shock measure, which similarly focuses on unexpected policy changes during FOMC meetings. Appendix Tables A.3–A.5 confirm that our main results are largely robust with these monetary policy shocks.

Other Monetary Policy Tightening Cycles Our economic narrative primarily focuses on the 2022 monetary tightening due to its unprecedented speed, the magnitude of rate hikes, and the accompanying slowdown in bank credit growth. The only other tightening cycle within our sample period (2012Q3–2023Q4) is the 2015–2018 cycle, which spanned from 2015Q4 to 2018Q4.

To test the generalizability of our findings, we conducted an exercise using a dummy variable for the 2015 tightening cycle. In untabulated results, we find that the effects are largely insignificant. This suggests that our proposed economic mechanism depends on both sharp rate hikes and significant tightening in bank lending. In contrast, the

2015–2018 cycle featured a gradual 225-basis-point increase over three years alongside continued loan expansion, with little evidence of tightening by banks. Without a contraction in bank credit, borrowers had no strong incentive to turn to BDCs, preventing the mechanism documented in our paper from materializing.

This exercise underscores the necessary conditions for our proposed mechanism: a substantial monetary shock combined with a meaningful contraction in bank credit.

Alternative Definition of Non-BDCs. Our baseline analysis in Table 3 classifies Y-14 loan-level data by borrowers into BDCs and non-BDC loans to examine how bank lending to BDC borrowers differed from lending to other firms during the 2022 monetary tightening cycle. To ensure robustness, we test alternative definitions of non-BDC borrowers.

Appendix Table A.6 confirms that our findings are little changed when we restrict the non-BDC sample to non-financial firms, excluding all BDCs and all Y-14 borrowers with a 3-digit NAICS code of 521 (Monetary Authorities-Central Bank) or 522 (Credit Intermediation and Related Activities). This restriction isolates our results from potential distortions arising from bank lending to other nonbanks.

Robustness Across Loan Types. We conduct two robustness tests to assess whether our findings hold across different loan types.

First, since credit line utilization can differ significantly from other loan types, our baseline estimates of utilization rates (Columns (2) and (5) in Table 3) focus on credit lines, which constitute the majority of bank loans to BDCs. We now extend our analysis to include all loan types. Appendix Table A.7 confirms that, across various specifications, BDC loan utilization remains higher than that of non-BDCs during monetary tightening, supporting our main results.

Second, in Table 5, where we show that banks face lower credit risk on loans to BDCs, we include all loan types. For robustness, we now restrict the analysis to credit lines. Appendix Table A.8 shows that our findings remain robust, with some estimates—such as those for loss given default—becoming even larger. This reinforces our conclusion that

BDCs mitigate banks' credit risk by providing more collateral and higher debt priority, securing funding even during monetary tightening.

Sub-Sample Analysis for Public and Private BDCs. In Section 2.2, we showed that privately held BDCs have driven much of the recent growth in direct lending, coinciding with their increased reliance on bank loans. This raises the concern that differences in bank financing reliance between private and public BDCs may be influencing our results.

Funding sources differ between private and public BDCs. Public BDCs raise capital primarily from retail investors through bond and equity issuance, while private BDCs—more akin to traditional private credit funds—depend on committed capital from high-net-worth individuals and institutional investors.[29] With limited access to capital markets, private BDCs rely more on bank credit lines to seize investment opportunities.

Fee structures may also impact bank financing demand. Public BDCs typically charge higher performance fees than private BDCs (Turner, 2019). Thus, despite having access to dry powder, private BDCs may use bank credit lines strategically—not just to fund investments but to enhance performance—depending on cash flow timing (Albertus and Denes, 2024).

To test whether our baseline findings on bank lending to BDCs (Tables 3 and 5) hold for both private and public BDCs, we re-estimate Eq. (1) on split samples. Appendix Tables A.9 (using *Tightening* as the monetary stance measure) and A.10 (using ΔFF_t) present the results. Across specifications, our key findings remain largely consistent for both BDC types. While coefficient estimates in Table A.10 suggest slightly stronger effects for private BDCs, the overall patterns confirm the robustness of our results. Importantly, since private BDCs closely resemble traditional private credit funds, the robustness of our findings for private BDCs suggests potential external validity for the broader private credit market.

[29] A key advantage of public BDCs over private BDCs or traditional private credit funds is their ability to diversify funding sources by incorporating retail capital while enabling managers to charge higher fees (Turner, 2019). More reputable fund managers are more likely to adopt the BDC structure (Jang, 2025). Indeed, many private BDCs transition to public status through an IPO as managers establish a track record or merge with an existing public BDC (O'Shea, Brown and Wathen, 2024). For example, MSC Income Fund announced its IPO in January 2025, while Golub Capital BDC, Inc., a public BDC, merged with Golub Capital BDC 3, Inc. on June 2024, with the former as the surviving entity.

Alternative Controls and Measures for BDCs' Reliance on Banks. In Section 5, we measure a BDC's reliance on bank financing using *BankLoanExpense*, the share of interest payments on bank loans relative to total interest expenses. To alleviate potential endogeneity concerns, we conduct robustness checks using alternative measures of bank reliance.

Appendix Table A.11 reports results from re-estimating Eq. (3) with two alternative definitions of bank reliance: (1) *High Bank Reliant* (Bank Loan Ratio) is a dummy variable equal to 1 if a BDC's utilized bank loan to total debt ratio is in the top quartile of the sample distribution. (2) *High Bank Reliant* (Utilization Rate) is a dummy variable equal 1 if a BDC's bank loan utilization rate is in the top quartile of the sample distribution, indicating heavy credit line drawdowns. Across both definitions, our key findings on BDC loan amounts and interest rates during tightening remain unchanged.

Since BDC characteristics and bank reliance evolve over time, we further test an alternative model incorporating additional BDC-level controls in estimating Eq. (3). Specifically, we include: total BDC assets, BDC leverage, bank loan commitment as a share of BDC's total assets, and bank loan commitment as a share of BDC's total debt. For example, including BDC leverage controls for time-variation in equity financing. Appendix Table A.12 confirms that our results remain robust under these alternative specifications.

Robustness with Khwaja-Mian Fixed Effect Specification In untabulated results, we confirm that our findings are robust to a more lenient fixed effects specification, ensuring they are not driven by highly specific variation. Specifically, our results hold under borrower × loan type and time fixed effects when the outcome is interest rate or loan amount, and under borrower and time fixed effects when the outcome is the term loan dummy. Furthermore, our findings remain unchanged when controlling for fixed vs. floating rate loans and a dummy indicating whether the base rate is tied to LIBOR, SOFR, PRIME, or another index.

7 Conclusion

This paper offers new evidence on how banks' financing of nonbanks shapes monetary policy transmission. Our paper makes several contributions. First, by merging supervisory bank loan-level data with deal-level private credit data, we trace—for the first time—the flow of credit from banks to BDCs and ultimately to firms. We show that during monetary tightening, banks reallocate lending to BDCs by expanding credit line limits through renegotiations, indirectly supporting credit supply. However, because banks charge BDCs higher interest rates—rates which are then passed on to end borrowers—this intermediation chain raises borrowing costs. In other words, while the extension of the credit chain mitigates the contraction in credit supply, it also amplifies the price channel of monetary policy.

Second, by directly observing individual bank loans to BDCs, we offer the first in-depth look at the rapidly growing segment of bank loans to private credit funds. Our detailed data reveal why banks shift lending toward private debt lenders during monetary tightening. Specifically, these loans command higher interest rates yet exhibit lower loss-given-default—reflecting strong collateralization and seniority. This combination of increased profitability and relatively lower risk underscores a key incentive behind the expanding bank–nonbank nexus.

Overall, our findings underscore how connectivity between banks and nonbanks influences monetary policy outcomes. Although nonbanks attenuate the contractionary effects of tightening by maintaining credit provision, higher borrowing costs mean that monetary policy still transmits effectively through the price channel. As nonbank lending continues to expand, these results provide important insight on how future policy changes might propagate through increasingly complex intermediation chains.

Looking ahead, our study suggests several avenues for further research. First, while we focus on a period of pronounced monetary tightening in 2022, exploring whether these transmission channels behave symmetrically during easing cycles would offer a more complete picture of the broader macroeconomic implications. Second, investigating how heterogeneity among nonbanks—such as varying funding structures, risk profiles, and regulatory frameworks—shapes their role in monetary policy transmission could yield important policy insights. As nonbank lending grows and evolves, understanding these dynamics will be essential for both researchers and policymakers.

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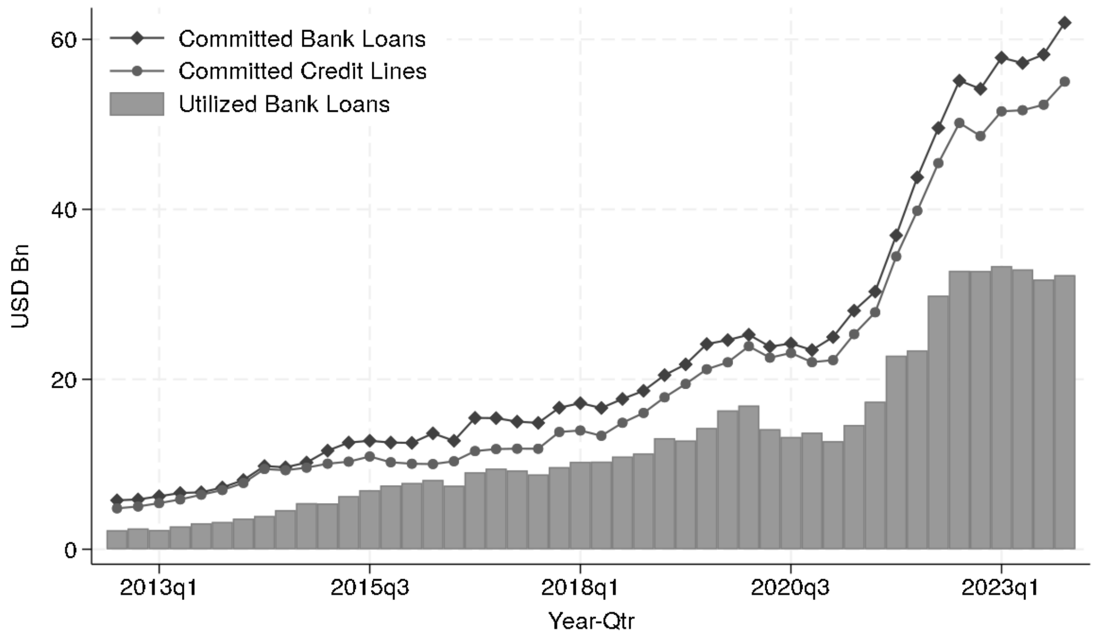
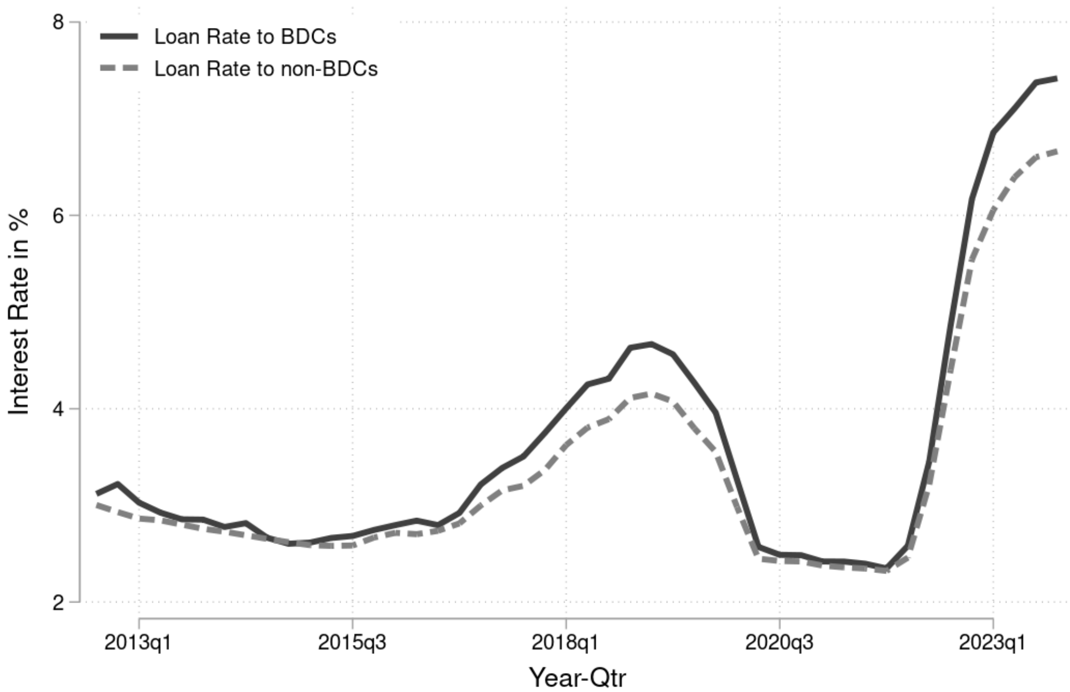
Figure 1. The Rise of Bank Credit Line Lending to BDCs



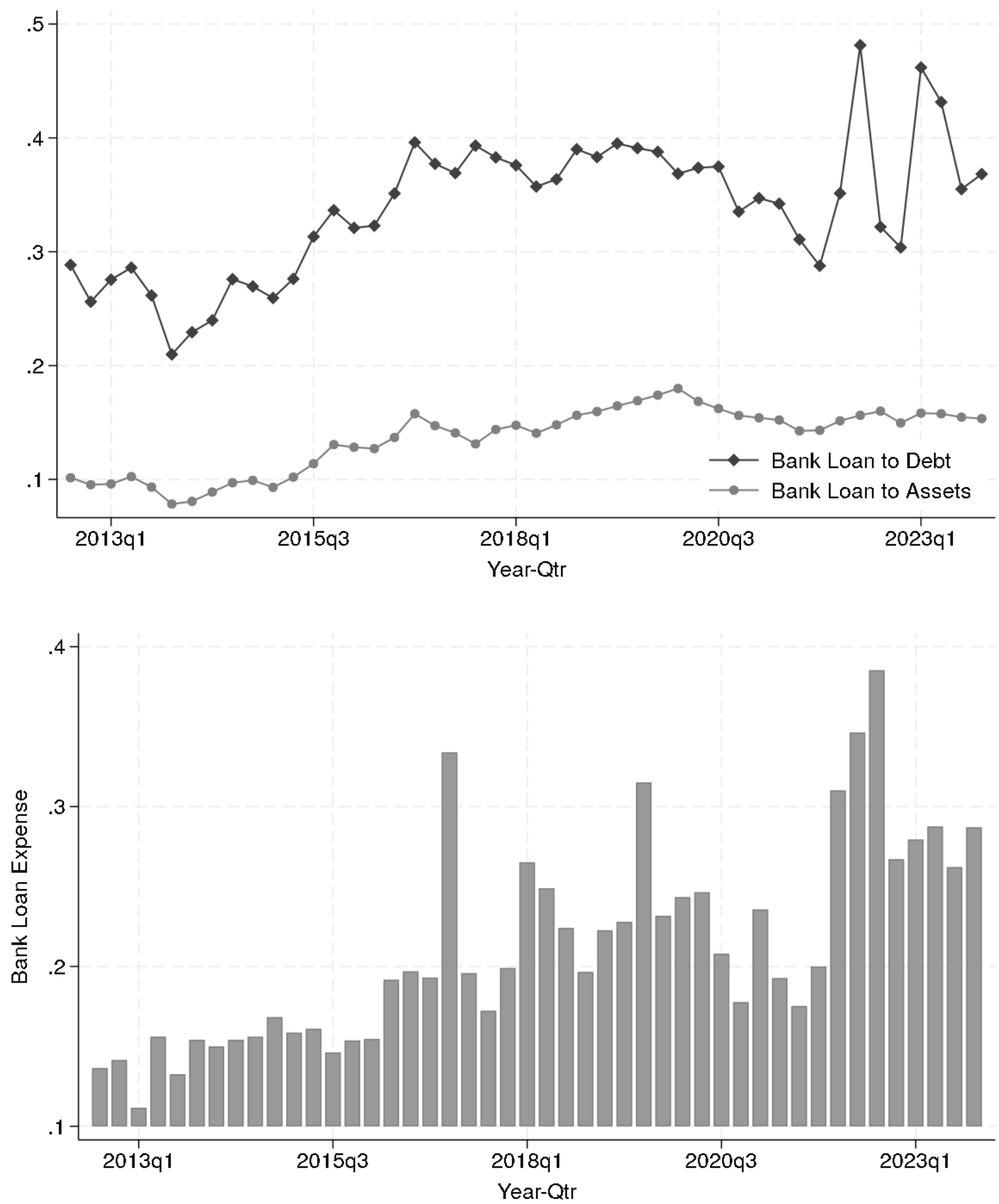
Notes: This figure illustrates the volume and composition of bank lending to BDCs. The dark line with diamond markers represents the aggregate dollar amount of committed bank loans, while the gray line with round markers indicates the aggregate dollar amount of committed bank credit lines. The bars show the aggregate dollar amount of utilized bank loans. On average, the commitment-weighted share of credit lines in bank loans to BDCs is 89%. Bank loans other than credit lines primarily consist of fronting exposures and term loans. This figure includes 142 unique public and private BDCs with outstanding bank commitments and 40 banks over the sample period 2012Q3–2023Q4.

Figure 2. Interest Rate on Bank Loans: BDCs versus non-BDCs



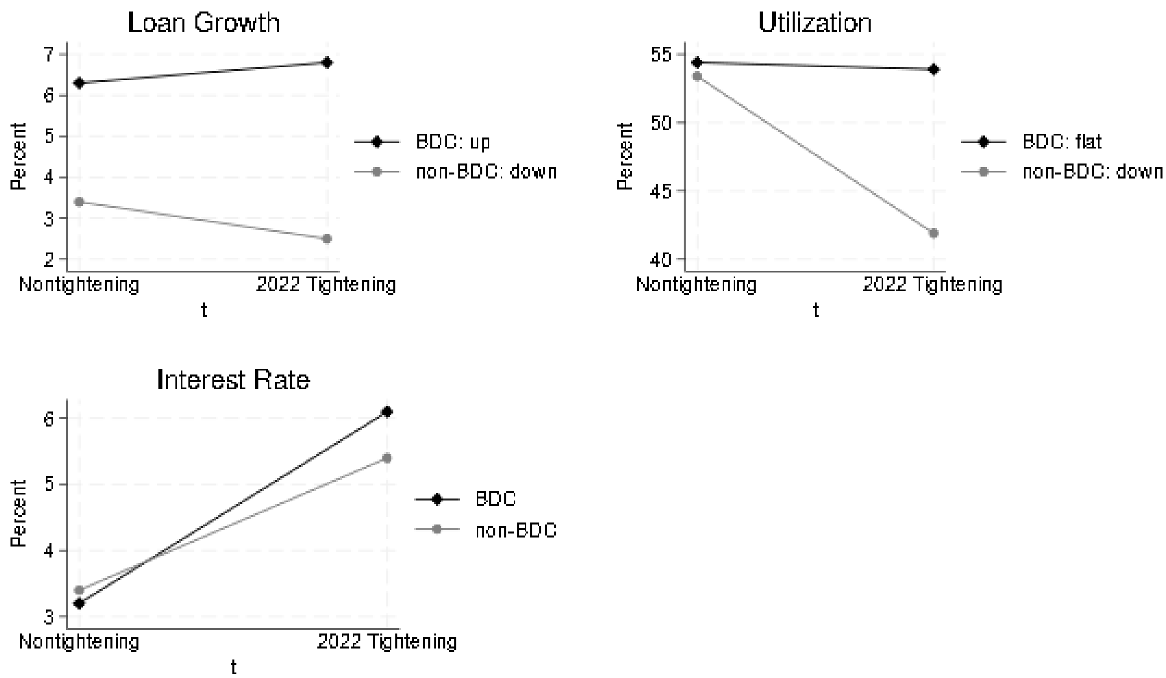
Notes: This figure plots the average time series of interest rates on bank loans to BDC and non-BDC borrowers. Quarterly average interest rates are weighted by the utilized amount, aggregated at the bank-borrower pair level, and expressed in percentage points. The sample period is 2012Q3–2023Q4.

Figure 3. BDCs' Financing: the increasing reliance on banks



Notes: This figure illustrates BDCs' increasing reliance on bank loans. The upper panel plots the average share of bank loan commitments relative to BDC debt and relative to BDC assets each quarter. The lower panel plots the average Bank Loan Expense—the share of total interest expenses attributable to interest payments on outstanding bank loans—each quarter. The sample period is 2012Q3–2023Q4, and the analysis includes 190 BDCs with available data.

Figure 4. Aggregate Patterns: bank lending to BDCs vs. other borrowers



Notes: This figure presents the mean values of key loan metrics, including the growth rate of loan commitments, utilization rate of credit lines, and loan interest rates for both non-tightening periods (when the Fed Funds rate did not increase) and the 2022 monetary tightening cycle (2022Q1–2023Q4). Using Y-14 loan-level data, loans are categorized by borrower type into BDC borrowers and non-BDC borrowers. For each borrower group and quarter, we compute the quarterly growth rate of total loan commitments, the average utilization rate of credit lines, and average loan interest rates. The reported values represent the average of these time series across the sample period. Table A.1 provides robustness checks based on alternative definitions of non-BDC borrowers.

Table 1. Summary Statistics: bank loans

	Count	Mean	SD	Median
Panel A: Bank Loans to BDCs				
Committed Loan Amount (USD Mn)	10,197	87.20	108.00	50.00
Utilized Loan Amount (USD Mn)	10,197	52.40	83.80	22.30
Interest Rate (%)	10,197	4.32	2.13	3.73
Maturity (Years)	10,197	5.71	2.53	5.00
Utilization Rate (only credit lines)	7,970	0.54	0.29	0.54
Term Loan Share	10,197	0.02	0.12	0.00
Credit Line Share	10,197	0.72	0.41	0.99
Δ $Log(Loan)$	7,232	0.01	0.31	0.00
$\mathbf{1}\times$(First Lien Senior Secured)	10,197	0.92	0.27	1.00
$\mathbf{1}\times$(Collateralized)	10,197	0.92	0.27	1.00
Loss Given Default	7,809	0.29	0.16	0.30
Probability of Default	7,817	0.01	0.04	0.00
Panel B: Bank Loans to Non-BDCs				
Committed Loan Amount (USD Mn)	7,991,557	13.24	23.02	3.60
Utilized Loan Amount (USD Mn)	7,991,557	7.78	13.69	2.36
Interest Rate (%)	7,991,557	3.89	1.89	3.57
Maturity (Years)	7,056,000	7.57	5.41	5.50
Utilization Rate (only credit lines)	2,941,337	0.50	0.35	0.50
Term Loan Share	7,991,557	0.31	0.44	0.00
Credit Line Share	7,991,557	0.33	0.45	0.00
Δ $Log(Loan)$	5,290,219	-0.00	0.28	-0.00
$\mathbf{1}\times$(First Lien Senior Secured)	7,991,557	0.84	0.37	1.00
$\mathbf{1}\times$(Collateralized)	7,991,557	0.86	0.35	1.00
Loss Given Default	5,762,070	0.33	0.19	0.33
Probability of Default	5,784,124	0.03	0.10	0.01

Notes: This table reports summary statistics for bank loans to BDCs (Panel A) and non-BDCs (Panel B). Unless otherwise stated, the data is at the loan-year-quarter level, covering the sample period 2012Q3–2023Q4. Committed Loan Amount *is the reported total loan commitment in a given credit facility.* Utilized Loan Amount *is the reported total loan utilized amount in a given credit facility.* Interest Rate *is the reported interest rate for a loan, expressed in percentage points.* Maturity *is the difference between maturity and origination date.* Utilization Rate *is the ratio of utilized to committed credit and is defined only for credit lines.* Credit Line Share *and* Term Loan Share *are borrower-time level aggregates and report the shares of that loan type in a given borrower's total bank debt.* Δ $Log(Loan)$ *is the log change in loan commitment at the bank-borrower level from quarter t relative to quarter $t-1$, expressed in decimal.* First Lien Senior Secured *Debt is a dummy equal to 1 if the borrower pledges a first lien senior secured claim on a given loan, and 0 if the loan is second lien, senior unsecured, or contractually subordinated.* Collateralized *is a dummy equal to 1 if the borrower pledges any collateral on a given loan, and 0 if the loan is uncollateralized (unsecured).*

Table 2. Summary Statistics: BDCs and loan portfolio

	Count	Mean	SD	Median
Panel A: BDC Loan-level				
Par Amount (USD M)	460,192	11.31	27.65	3.95
Maturity (Years)	452,231	4.14	2.01	4.17
All-In Yield (%)	438,545	9.38	2.89	9.36
Cash Spread (%)	442,130	6.68	2.80	6.25
Cash+PIK Spread (%)	442,130	7.19	3.64	6.50
$\mathbf{1}\times$(Nonaccrual Loan)	460,170	0.03	0.16	0.00
$\mathbf{1}\times$(First Lien Debt)	460,192	0.83	0.37	1.00
$\mathbf{1}\times$(Fixed Rate Loan)	460,192	0.12	0.33	0.00
Panel B: BDC-level				
Total Assets (USD M)	3,997	1479.04	3267.61	572.68
Total Debt/Total Assets	3,997	0.40	0.48	0.43
Bank Loan Commitment/ Total Assets	3,997	0.14	0.33	0.06
Bank Loan Commitment/ Total Debt	3,996	0.60	7.45	0.13
Utilized Bank Loan/ Total Debt	3,996	0.19	0.27	0.05
Bank Loan Expenses	3,553	0.23	0.48	0.07

Notes: This table reports summary statistics for BDC portfolios as well as BDCs' financials. Data is at the loan-quarter level for Panel A and BDC-quarter level for Panel B, covering the sample period 2012Q3–2023Q4. Par Amount *is the reported face value of the loan.* Maturity *is the reported maturity of the loan as of the holding date (not origination date) expressed in years.* All-in-Yield *is the reported total interest rate on a given loan, expressed in percentage points.* Cash Spread *is the standard credit spread on the loan over the base rate.* Cash + PIK Spread *includes the additional spread if a given loan has a PIK option.* I(First Lien Debt) *is an indicator variable equal to 1 if the loan is a first lien debt investment, and 0 otherwise.* I(Non-Acrual) *is an indicator variable equal to 1 if the loan is non-accruing, and 0 otherwise.* I(Fixed Rate Loan) *is an indicator variable equal to 1 if a given loan is fixed interest rate, and 0 otherwise.* Bank Loan Expense *is the share of total interest expenses that is attributable to interest payments on outstanding bank loans.*

Table 3. Baseline Regressions: bank lending to BDCs vs. other borrowers

	ΔLog Loan	Utilization	Interest Rate	ΔLog Loan	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times Tightening$	0.011**	0.142***	0.009***			
	(0.004)	(0.027)	(0.002)			
$BDC \times \Delta FF_t$				0.709*	9.372***	0.532***
				(0.400)	(2.154)	(0.112)
BDC	0.001	0.044**	0.002**	0.003	0.071***	0.004***
	(0.003)	(0.019)	(0.001)	(0.003)	(0.017)	(0.001)
R-squared	0.028	0.286	0.480	0.028	0.286	0.480
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,653,826	1,712,362	3,468,670	3,653,826	1,712,362	3,468,670

$^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$

Notes: This table reports regression results from Eq. (1) *. The sample period is 2012Q3–2023Q4, with data at the bank-borrower-year-quarter level.* Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF_t *is changes in the effective federal funds rate. BDC is an dummy equal to 1 if the borrower is a BDC, and 0 otherwise.* Δ Log Loan *is the log change in loan commitment between bank b and borrower i in time t relative to time* $t-1$*, and expressed in decimal.* $Utilization$ *is the ratio of utilized to committed loans, and is restricted to credit lines.* $InterestRate$ *is the weighted average interest rate across all utilized loans between a given b and i in time t, expressed in decimal.* $CreditRating$ *is bank's internal credit ratings, which is bank-specific, time-varying, and captures bank-estimated ex-ante credit risk. Firm level controls enter the regressions with a one-period lag and include bank-estimated probability of default, expected loss given default, share of term loans in total bank debt, share of credit lines in total bank debt, and the natural log of total bank debt in* $t-1$*. Standard errors are double clustered at bank* $\times$ *borrower and YearQtr level.*

Table 4. The Renegotiation Channel: panel A

Panel A: Increases in Credit Line Limits by Banks

$Y_{i,b,t}$: Δ *Log (Loan)*	(1)	(2)	(3)	(4)	(5)	(6)
BDC $\times$ *Tightening*	0.012**	0.047***	-0.622			
	(0.005)	(0.013)	(0.382)			
BDC $\times$ ΔFF_t				0.810**	2.648***	-28.915***
				(0.381)	(0.925)	(8.621)
BDC	0.001	-0.011	0.483	0.004	0.002	0.159
	(0.003)	(0.008)	(0.376)	(0.003)	(0.007)	(0.198)
R-squared	0.046	0.256	0.204	0.046	0.256	0.204
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
Credit Line Sample	Existing	Limit Expanded	New	Existing	Limit Expanded	New
N	1,533,250	295,176	4993	1,533,250	295,176	4993

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This panel reports regression results from Eq. (1). *The sample period is 2012Q3–2023Q4, with data at the bank-borrower-year-quarter level. The sample is restricted to credit lines only. Columns (1) and (4) exclude newly originated credit lines and examine only* pre-existing *credit lines. Columns (2) and (5) restrict the sample to pre-existing credit lines conditional on* any *positive change in credit line commitment in time t relative to* $t-1$. *Columns (3) and (6) focus on newly originated credit lines only.* Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF_t *is changes in the effective federal funds rate. BDC is an dummy equal to 1 if the borrower is a BDC, and 0 otherwise.* Δ Log Loan *is the log change in loan commitment between bank b and borrower i in time t relative to time* $t-1$, *and expressed in decimal. CreditRating is bank's internal credit ratings, which is bank-specific, time-varying, and captures bank-estimated ex-ante credit risk. Firm-level controls enter the regressions with a one-period lag and include bank-estimated probability of default, expected loss given default, share of term loans in total bank debt, share of credit lines in total bank debt, and the natural log of total bank debt in* $t-1$. *Standard errors are double clustered at bank* $\times$ *borrower and YearQtr level.*

Table 4. The Renegotiation Channel: panel B

Panel B: Credit Line Utilization by Borrowers

$Y_{i,b,t}$: Δ *Log* (*CL Utilization*)	(1)	(2)	(3)	(4)	(5)	(6)
BDC $\times$ *Tightening*	0.113*	0.105*	0.266***			
	(0.061)	(0.057)	(0.080)			
BDC $\times$ ΔFF_t				7.810**	5.853	15.883**
				(3.587)	(3.823)	(5.989)
BDC	0.038	0.036	0.042	0.059*	0.058*	0.109**
	(0.035)	(0.035)	(0.052)	(0.032)	(0.031)	(0.046)
R-squared	0.032	0.035	0.097	0.032	0.035	0.097
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
Credit Line Sample	All	Existing	Limit Expanded	All	Existing	Limit Expanded
N	1,667,709	1,533,250	295,187	1,667,709	1,533,250	295,187

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This panel reports regression results from Eq. (1). *The sample period is from 2012Q3–2023Q4, with data at the bank-borrower-year-quarter level. The sample is restricted to credit lines only. Columns (1) and (4) focus on all credit lines. Columns (2) and (5) exclude newly originated credit lines and examine only* pre-existing *credit lines. Columns (3) and (6) restrict the sample to pre-existing credit lines conditional on* any *positive change in credit line commitment in time t relative to* $t-1$. Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF_t *is changes in the effective federal funds rate. BDC is an dummy equal to 1 if the borrower is a BDC, and 0 otherwise.* Δ Log (CL Utilization) *is the log change in credit line utilization between bank b and borrower i in time t, relative to time* $t-1$*, and expressed in decimal. CreditRating is bank's internal credit ratings, which is bank-specific, time-varying, and captures bank-estimated ex-ante credit risk. Firm-level controls enter the regressions with a one-period lag and include bank-estimated probability of default, expected loss given default, share of term loans in total bank debt, share of credit lines in total bank debt, and the natural log of total bank debt in* $t-1$*. All regressions also control for the contemporaneous total bank loan commitment between a given bank-borrower pair. Standard errors are double clustered at bank* $\times$ *borrower and YearQtr level.*

Table 5. Why Do Banks Prefer Lending to BDCs over Lending to Firms?

	1st Lien Senior Secured		Collateralized		Loss Given Default		Probability of Default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDC × *Tightening*	0.103***		0.103***		-0.027**		0.002	
	(0.020)		(0.020)		(0.011)		(0.002)	
BDC × ΔFF_t		5.910***		6.227***		-2.397***		0.154
		(1.534)		(1.436)		(0.593)		(0.118)
BDC	0.282***	0.304***	0.284***	0.305***	-0.083***	-0.087***	0.002***	0.002***
	(0.017)	(0.016)	(0.017)	(0.017)	(0.013)	(0.012)	(0.001)	(0.001)
R-squared	0.265	0.265	0.261	0.261	0.495	0.495	0.857	0.857
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3,653,826	3,653,826	3,653,826	3,653,826	3,676,199	3,676,199	3,678,000	3,678,000

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports regression results from Eq. (1). The sample period is 2012Q3–2023Q4, with data at the bank-borrower-year-quarter level. 1st Lien *is a dummy equal to 1 if the lender has a 1st lien senior secured claim on the borrower's assets in case of default;* Collateralized *is a dummy equal to 1 if the lender has a collateralized claim on the borrower's assets in case of default;* Loss Given Default *is ex-ante bank-reported estimate of loss given default;* Probability of Default *is ex-ante bank-reported estimate of default probability at the borrower level; all four variables above is obtained by averaging across all commitments between b and i in time t.* Tightening *is a dummy equal to 1 during monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF_t *is changes in the effective federal funds rate. BDC is an dummy equal to 1 if the borrower is a BDC, and 0 otherwise. CreditRating is bank's internal credit ratings, which is bank-specific, time-varying, and captures bank-estimated ex-ante credit risk. Firm level controls enter the regressions with a one period lag. In columns (1)–(4), these include bank-estimated probability of default, expected LGD, share of term loans in total bank debt, share of credit lines in total bank debt, and natural log of total bank debt. In columns (5)–(6), the controls remain the same, except expected loss is omitted to avoid using the lagged dependent variable (as expected loss is the product of loss given default, probability of default, and expected exposure at default). In columns (7)–(8), probability of default is omitted for the same reason, and expected loss is replaced with loss given default. Standard errors are double clustered at bank* × *borrower and YearQtr level.*

Table 6. BDC Loans vs. Bank Loans to Overlapping Borrowers: panel A

Panel A: Full Sample of Overlapping Borrowers

	Interest Rate				Loan Amount		**1**(Term Loan)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BDC \times Tightening$	0.521***	0.516***	0.547***	0.575***	0.252***	0.244**	0.406***	0.358***
	(0.116)	(0.117)	(0.118)	(0.120)	(0.093)	(0.095)	(0.060)	(0.060)
BDC	0.949***	0.978***	0.924***	0.909***	-0.378***	-0.384***	0.145**	0.198***
	(0.096)	(0.097)	(0.094)	(0.095)	(0.080)	(0.080)	(0.063)	(0.064)
$Log\ (1 + PIK\ Spread)$			0.790***	1.039***		0.119**		0.016
			(0.110)	(0.132)		(0.048)		(0.012)
$Log\ (1 + PIK\ Spread) \times Tightening$				-0.453***		0.064		0.016
				(0.157)		(0.058)		(0.014)
R-squared	0.924	0.924	0.932	0.932	0.604	0.605	0.525	0.566
Firm x YrQtr x Loan-Type FE	Y	Y	Y	Y	Y	Y	-	-
Firm x YrQtr FE	-	-	-	-	-	-	Y	Y
Debt Seniority FE	N	Y	Y	Y	N	Y	N	Y
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	309,692	309,295	308,962	308,962	309,692	308,962	472,319	471,807

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports regression results from estimating Eq. (2). The sample period is 2012Q3–2023Q4, with data at the loan-year-quarter level. Interest Rate *is the reported interest rate, expressed in percentage points.* Loan Amount *is the natural log of the utilized amount of the loan.* 1(Term Loan) *is a dummy equal to 1 if a loan is a term loan, and 0 otherwise.* BDC *is a dummy equal to 1 if the loan is provided by a BDC, 0 if provided by a bank.* PIK Spread *is time-varying payment-in-kind spread for BDC loans, and is set to 0 for bank loans.* Loan-type *FE is 1 for term loans, 2 for credit lines, and 3 for other loans types.* Debt Seniority FE *are indicators for first lien senior secured debt, second lien senior secured debt, and junior/unsecured debt. Columns (1)–(4) control for utilized loan amount, maturity, and non-accrual status, while Columns (5)–(8) control for loan interest rate, maturity, and non-accrual status. Standard errors are double-clustered at the borrower and YearQtr levels.*

Table 6. BDC Loans vs. Bank Loans to Overlapping Borrowers: panel B

Panel B: Splitting Overlapping Borrowers by Bank Lending Constraints

	Interest Rate				Loan Amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDC × *Tightening*	0.827***	0.380***			0.295***	0.179		
	(0.194)	(0.129)			(0.080)	(0.120)		
BDC × ΔFF_t			61.480***	21.730**			15.553***	11.544
			(13.774)	(8.987)			(4.831)	(6.954)
BDC	1.093***	0.887***	1.293***	1.039***	-0.591***	-0.252**	-0.511***	-0.185**
	(0.137)	(0.112)	(0.127)	(0.095)	(0.068)	(0.101)	(0.060)	(0.082)
R-squared	0.885	0.924	0.884	0.924	0.599	0.602	0.598	0.602
Firm x YrQtr x Loantype FE	Y	Y	Y	Y	Y	Y	Y	Y
Debt Seniority FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank Loan Constrained	Y	N	Y	N	Y	N	Y	N
N	36,407	272,888	36,407	272,888	36,407	272,888	36,407	272,888

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table presents regression results from estimating Eq. (2) by splitting the sample of overlapping borrowers into those likely facing bank lending constraints and those that do not. A borrower-quarter is classified as "Bank Loan Constrained" if the one-period lagged utilization rate of bank loans exceeds the 75th percentile of the sample distribution, indicating the borrower has nearly exhausted its bank borrowing capacity. The sample period is 2012Q3–2023Q4, with data at the loan-year-quarter level. Interest Rate *is the reported interest rate, expressed in percentage points.* Loan Amount *is the natural log of the utilized amount of the loan.* BDC *is a dummy equal to 1 if the loan is provided by a BDC, 0 if provided by a bank.* Loan-type *FE is 1 for term loans, 2 for credit lines, and 3 for other loans types.* Debt Seniority FE *are indicators for first lien senior secured debt, second lien senior secured debt, and junior/unsecured debt. Columns (1)–(4) control for utilized loan amount, maturity, and non-accrual status, while Columns (5)–(8) control for loan interest rate, maturity, and non-accrual status. Standard errors are double-clustered at the borrower and YearQtr levels.*

Table 7. BDCs' Reliance on Bank Financing and Monetary Pass Through

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
$Tightening \times BankLoanExpense$	0.428***		0.313***	
	(0.121)		(0.0735)	
$\Delta FF_t \times BankLoanExpense$		21.55**		9.056**
		(10.47)		(3.881)
$BankLoanExpense$	-0.442***	-0.247***	-0.231***	-0.0857**
	(0.126)	(0.0879)	(0.0633)	(0.0390)
R-squared	0.501	0.501	0.559	0.559
BDC, Yr-Qtr FE	Y	Y	Y	Y
Loan-Type FE	Y	Y	Y	Y
Loan Controls	Y	Y	Y	Y
N	353,559	353,559	341,009	341,009

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports regression results from estimating Eq. (3). The sample period is 2012Q3–2023Q4, with data at the BDC-loan-year-quarter level. The dependent variable is $Loan\ Amount$ (the natural log of the loan's face value in dollars) in columns (1)–(2) and $Interest\ Rate$ (the interest rate on a given loan, expressed in percentage points) in columns (3)–(4). BankLoanExpense *is the share of total interest expenses attributable to interest payments on outstanding bank loans for a given BDC in a given quarter.* Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF_t *is changes in the effective federal funds rate, expressed as a decimal. Control variables include BDC total assets, loan maturity, and an indicator variable capturing non-accrual status of the loan. Standard errors are double-clustered at the borrower and YearQtr levels.*

Appendix

A.1 Variable Definitions

Variable definitions are categorized into Y-14 loan-level, Y-14 firm-level, BDC loan-level, and BDC-level variables.

Y-14 Loan-Level Variables.

- *Committed Loan Amount:* Reported total loan commitment in a given credit facility.
- *Utilized Loan Amount:* Reported total loan utilized amount in a given credit facility.
- *Interest Rate:* Reported interest rate, expressed as a decimal. For regression analysis, it is aggregated to the bank-borrower-time level, weighted by the utilized loan amount.
- *Maturity:* Difference between loan maturity date and loan origination date, expressed in years.
- *Utilization Rate:* Ratio of utilized loan amount to committed loan amount.
- *Term Loan Share:* Share of term loan commitment as a fraction of total bank loan commitment.
- *Credit Line Share:* Share of credit line commitment as a fraction of total bank loan commitment.
- $\Delta\ Log(Loan)$: Log quarterly change in total loan commitment at the bank-borrower level.
- $\mathbf{1}\times$*(First Lien Senior Secured):* Indicator variable equal to 1 if the borrower pledged a first lien senior secured claim on a given loan. For regression analysis, it is aggregated to the bank-borrower-time level.
- $\mathbf{1}\times$*(Collateralized):* Indicator variable equal to 1 if the borrower pledged any collateral on a given loan. For regression analysis, it is aggregated to the bank-borrower-time level.
- *Loss Given Default:* Expected loan recovery rate upon default estimated by the reporting bank.
- *Probability of Default:* Banks' internal estimates of borrower's 1-year ahead probability of default.
- $\mathbf{1}\times$*(Term):* Indicator variable equal to 1 if the loan is a term loan.

Y-14 Firm-Level Variables.

- *Total Assets:* Book value of current year assets (USD Mn).
- *Return on Assets:* Ratio of EBITDA to book value of total assets, also referred in main text as earnings or firm profitability.
- *Liquidity:* Ratio of Cash and Marketable Securities to Total Assets.
- *Tangibility:* Ratio of tangible assets to total assets.
- *Debt/Assets:* Ratio of total debt to total assets.
- *Debt/EBITDA:* Ratio of total debt to EBITDA.
- *Sales:* Net sales for the current year (USD Mn).
- *EBITDA:* EBITDA for the current year (USD Mn).
- *Credit Rating:* Bank's internal credit ratings, which is at the borrower-level, bank-specific, time-varying, and captures bank-estimated ex-ante credit risk.
- *Bank Loan Commitment/Total Assets:* Ratio of bank loan commitment to total assets.
- *Overlapping-Borrowers:* Borrowers that have both BDC debt and bank debt, including completely undrawn bank loan commitments.

BDC Loan-Level.

- *Par Amount:* Reported face value of the loan (USD Mn).
- *All-In Yield:* Reported total interest rate on a given loan, expressed in percentage points.
- $\mathbf{1}\times$*(Term):* Indicator variable equal to 1 if the loan is a term loan.
- *Cash Spread:* Standard credit spread on the loan on top of the base rate, expressed in percentage points.
- *Cash+PIK Spread:* Sum of cash spread and the additional PIK spread if a given loan has a PIK option, expressed in percentage points.
- *Maturity:* Reported loan maturity as of the holding date (not origination).
- $\mathbf{1}\times$*(Non-accrual):* Indicator variable equal 1 if the given loan is reported as non-accruing.

BDC-Level Variables.

- *Bank Loan Expense:* For a given BDC in a given quarter, the share of total interest expenses that is attributable to interest payments on outstanding bank loans. Constructed by merging BDC Collateral and Y-14.

- *Bank Reliance:* For a given BDC in a given quarter, an indicator variable equal to 1 if the BDC's bank loan utilization rate is above the 75th percentile of the sample distribution across all BDCs and over time. Constructed by merging BDC Collateral and Y-14.

- *BDC Leverage:* The ratio of total debt to total assets.

Monetary Policy Series.

- *Tightening:* A dummy variable equal 1 for the 2022 monetary tightening cycle (2022Q1–2023Q4).

- ΔFF*:* Changes in the Federal Funds rate, expressed as a decimal.

- *MP Shock:* The sum of monetary Policy shocks reported by Jarociński and Karadi (2020) and Bauer and Swanson (2023) from quarter $t-1$ through quarter t.

A.2 Y-14 Data Cleaning

- The Y-14 H.1. data was downloaded in January 2024. Following Greenwald et al. (2024) and Chodorow-Reich, Darmouni, Luck and Plosser (2022), we identify distinct firms using Taxpayer Identification Number (TIN), allowing us to link the same firm across banks and over time. This addresses cases when a firm borrows from multiple banks, which may use different naming conventions for the same borrower.

- Some borrowers have missing TIN. We apply a name-standardization algorithm to obtain a clean and uniform set of firm names. If a TIN is missing, we fill in missing observations if the bank reports a consistent TIN in any portion of the loan data; for multi-bank borrowers for which one bank does not report a TIN, we use a consistent TIN reported by other banks.

- Unless otherwise stated, all variables are winsorized at the 2.5 and 97.5 percent levels, following Favara, Minoiu and Perez-Orive (2022), to mitigate the influence of outliers and potential reporting errors.

- We exclude observations with negative or zero values for committed loan amount, negative values for utilized loan amount, or cases where committed loan amount is less than utilized amount.

- We drop all facility records with origination dates before 1990 or maturities greater than 30 years to minimize the influence of potential data entry errors.

- To ensure data accuracy in interest rate calculations, we exclude observations with interest rates below 0.5 percent or above 50 percent to minimize the influence of potential data entry errors.
- When using firm's reported financial variables, we exclude financial statement information if the financial statement date is missing or comes after the reporting date. We also exclude likely data errors by imposing the following conditions: (i) EBITDA does not exceed net sales, (ii) fixed assets exceed total assets, (iii) cash and marketable securities do not exceed total assets, (iv) long-term debt does not exceed total liabilities, (v) short-term debt does not exceed total liabilities, (vi) tangible assets do not exceed total assets, (vii) current assets do not exceed total assets, and (viii) current liabilities do not exceed total liabilities.

A.3 BDC Collateral Data Cleaning

- The BDC Collateral data is reported at the BDC loan-quarter level, providing detailed information on borrower, lender, reporting period, par amount of the loan, all-in-yield, maturity, seniority, loan type (term loan, revolver, unitranche, etc) investment type (equity vs. various types of debt: first lien, second lien, subordinated), non-accruing status, among other details.
- We start the sample from 2012Q3, exclude exposures classified as 'Equity', and retain only debt investments (i.e. loans).
- Loans with a par amount above the 99th percentile are dropped to mitigate the impact of potential outliers.
- We drop loans missing interest rate data (i.e., all-in-yield) and those where the lien is classified as 'Other'. Additionally, loans with reported interest rates below 0.5% or above 50% are excluded.
- Facility records with origination dates before 1990 and maturities exceeding 30 years are removed to minimize potential data entry errors.
- We exclude one lender from the BDC sample that, based on discussions with industry experts, is not a typical middle-market private credit lender but instead specializes in SBA-guaranteed debt financing for very small businesses. Retaining this lender does not affect our results.
- We also obtain BDC quarterly financial data from BDC Collateral, which provides full coverage of major financial statement items—such as total assets, total debt, total investments, cash, and net income. However, it does not fully cover interest expense, as not all BDCs report this item. In BDC Collateral, interest expense is available for 87.6% of BDC-quarter observations.
- To supplement this, we merge data from Compustat for public BDCs, increasing total interest expense coverage to 92.5%. We manually verify a randomly selected sample, confirming that the remaining missing observations were indeed reported

as zero in Compustat for public BDCs or in the respective SEC filings for private BDCs. Notably, the median leverage of BDCs with missing interest expense is 4.6%, significantly lower than the 44.2% median leverage for the full sample. This suggests that these BDCs do not report interest expense as a material expense because they do not rely heavily on debt. Accordingly, we set the remaining missing interest expense data to zero. Our results remain unchanged when excluding these missing observations.

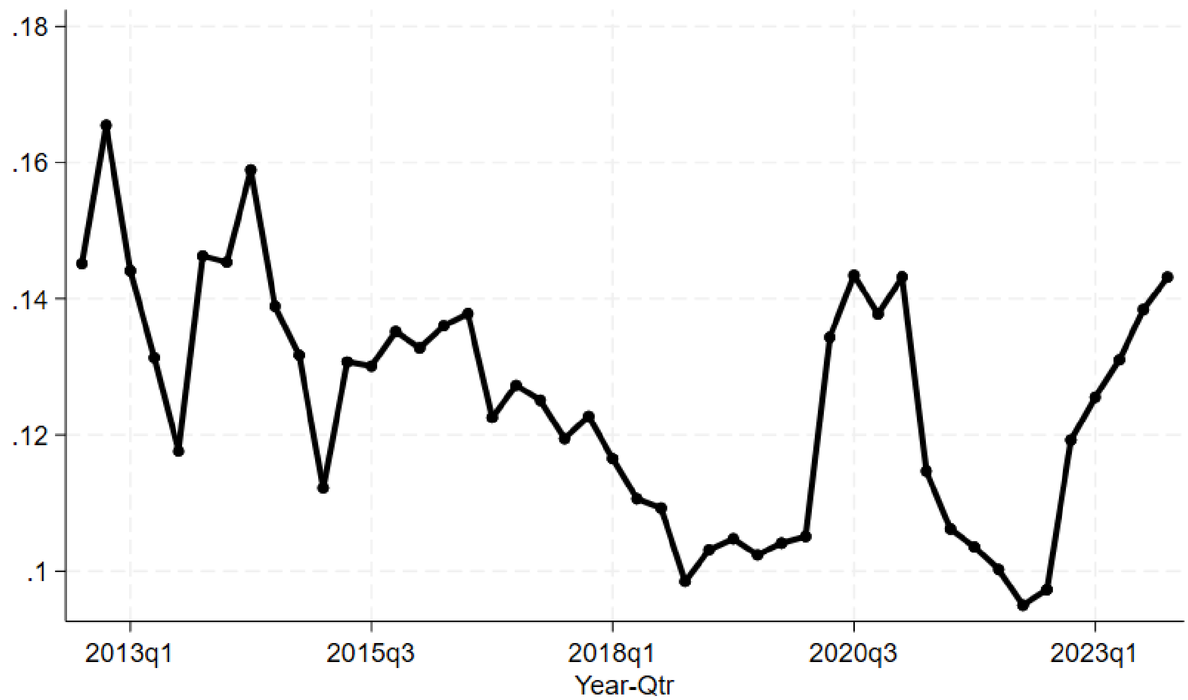
- To evaluate whether BDC borrowers in Refinitiv's BDC Collateral data are representative of the broader private credit market, we perform a balance test comparing key characteristics of BDC borrowers in our sample with private credit borrowers from Jang (2025) over the period 2014Q3–2023Q4. The table below presents the balance test results, examining borrowers' likelihood of obtaining a first-lien loan and the average interest rate spread (cash + PIK). The mean differences between the two groups are not statistically significant, even at the 10% level (assuming unequal variances).

Balance Test: BDC borrowers vs. private credit borrowers

	BDC			Private credit			Mean Difference
	N	Mean	SD	N	Mean	SD	
First-lien	11731	0.894	0.307	6605	0.895	0.306	-0.001
Interest rate spread (%)	11731	7.362	2.776	6605	7.300	2.709	0.062

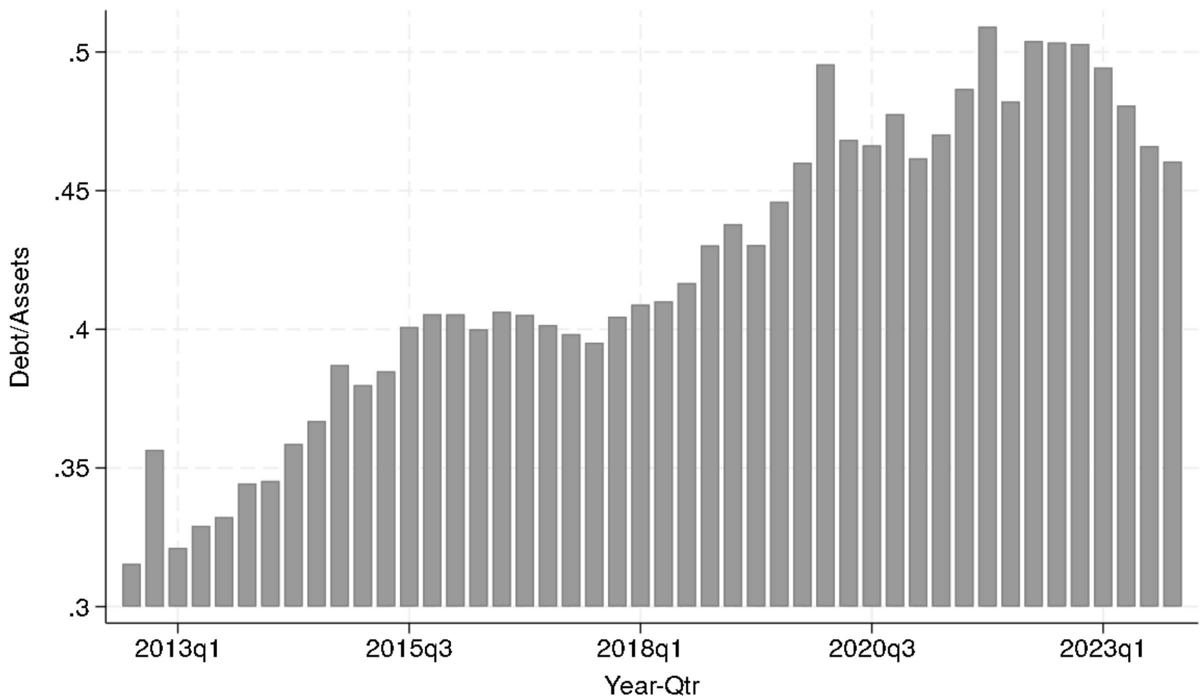
A.4 Additional Figures

Figure A.1. Fraction of BDC loans with PIK spread



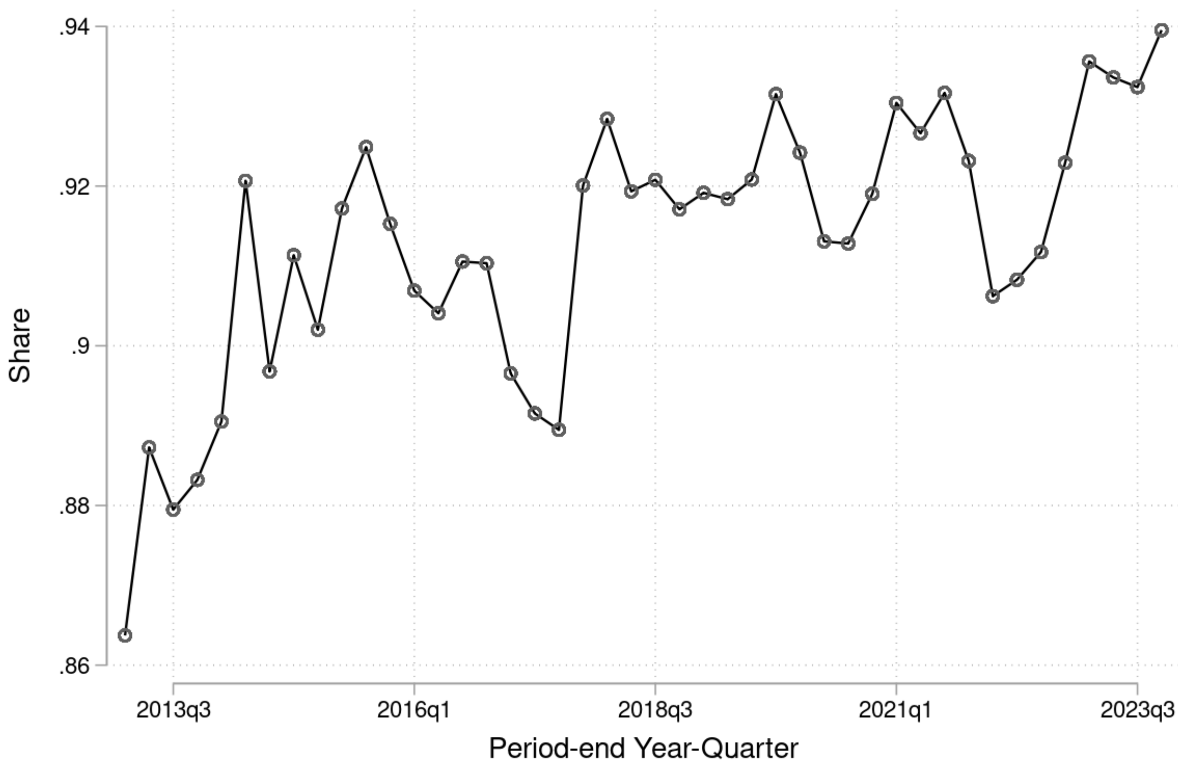
Notes: This figure plots the fraction of BDC loans with a non-zero payment-in-kind (PIK) spread from 2012Q3 to 2023Q4, weighted by loan amount. PIK allows borrowers to defer interest payments until maturity, typically in exchange for higher interest rates, providing borrowers with greater flexibility in cash flow management.

Figure A.2. BDC Leverage



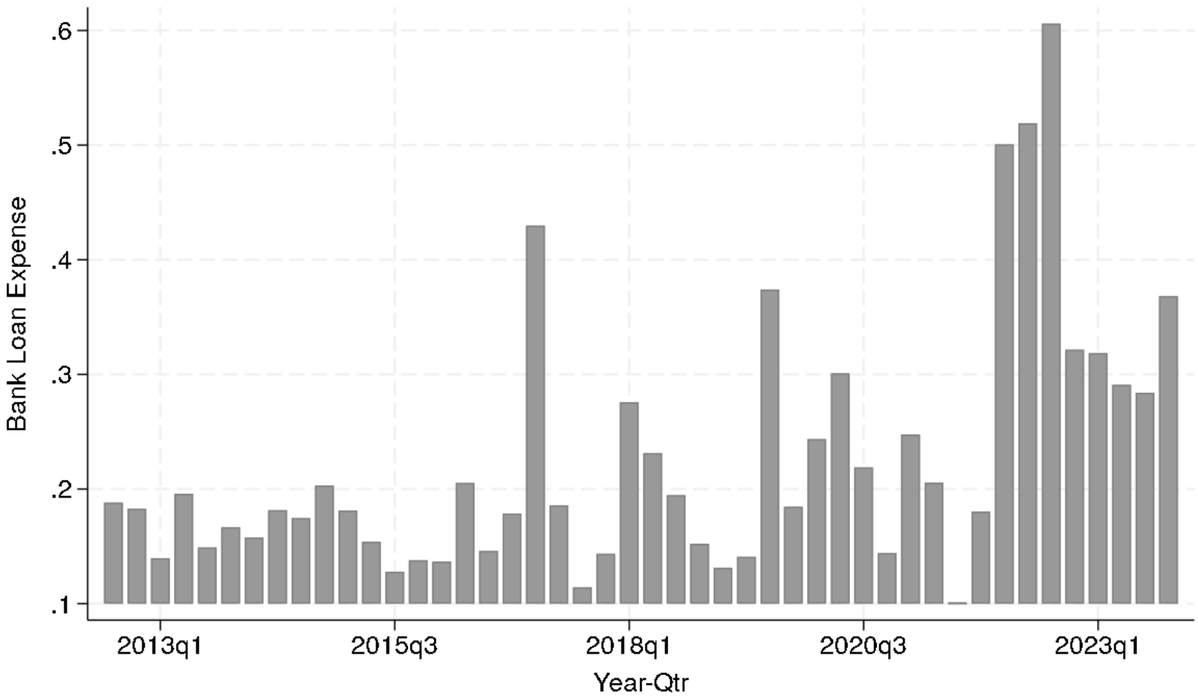
Notes: This figure plots the time series of the average BDC Leverage (Debt/Asset) weighted by BDC assets. The sample period is 2012Q3–2023Q4. The sample includes 190 BDCs with available data.

Figure A.3. Share of BDC Loans Held by Bank-Reliant BDCs



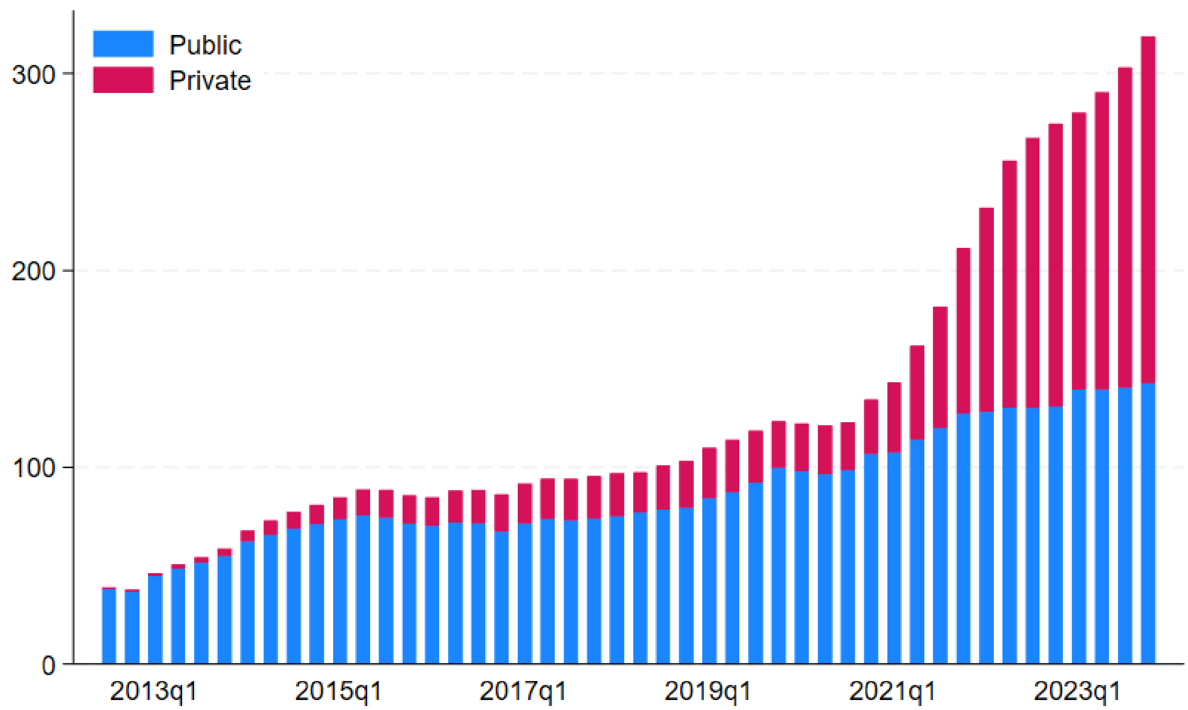
Notes: This figure plots the share of total BDC credit provided by Y-14 bank-reliant BDCs. Credit amount refers to the total par value of loans at a given time for each BDC. Bank-reliant BDCs are those with a non-zero loan commitment from a bank. The sample period spans 2012Q3 to 2023Q4, with 142 unique bank-reliant BDCs.

Figure A.4. Bank Loan Expense Ratio for Smaller BDCs



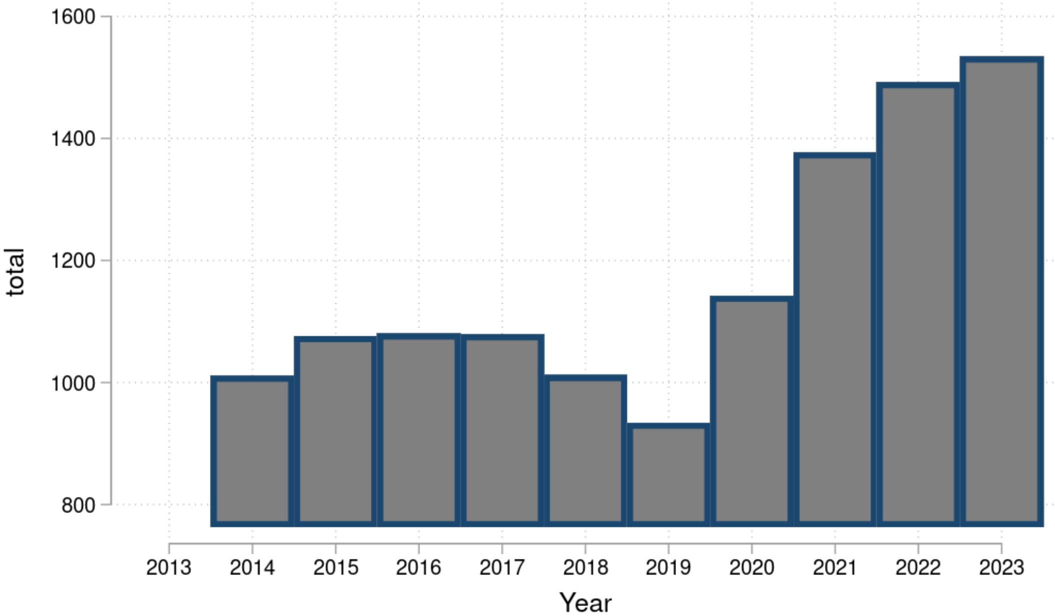
Notes: This figure illustrates BDCs' reliance on bank loans by plotting the average Bank Loan Expense—the share of total interest expenses attributable to interest payments on outstanding bank loans—each quarter. To emphasize small BDCs' dependence on banks, we restrict the sample to BDCs with total assets below the median and compare it with the full sample in Figure 3. The sample period is 2012Q3–2023Q4.

Figure A.5. Assets of Public and Private BDCs



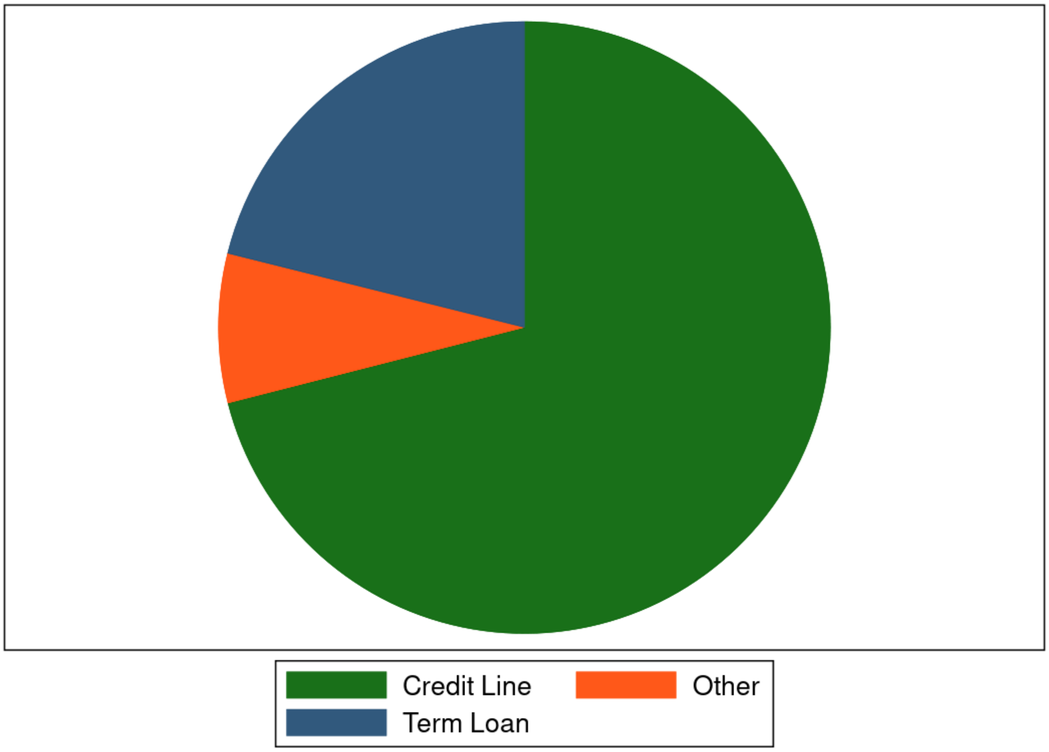
Notes: This figure plots the total assets (USD billions) of public and private BDCs over time, based on BDC Collateral data. The sample period spans 2012Q3–2023Q4.

Figure A.6. Overlapping Borrowers with both Bank Loans and BDC Credit



Notes: This figure shows the number of unique overlapping borrowers in our sample over time. Overlapping borrowers are firms that simultaneously hold bank loans and BDC credit in a given quarter, where bank loans include both drawn and undrawn commitments. The sample contains 4,793 unique overlapping borrowers.

Figure A.7. Bank Loan Type to Overlapping Borrowers



Notes: This figure shows the composition of bank loans to overlapping borrowers by loan type, weighted by loan commitment amount. Overlapping borrowers are firms that simultaneously hold bank loans and BDC credit in a given quarter, where bank loans include both drawn and undrawn commitments. The sample contains 4,793 unique overlapping borrowers.

A.5 Additional Tables

Table A.1. Robustness to Figure 4: alternative definitions of other borrowers

	BDC	Other Borrowers		
	(1)	(2)	(3)	(4)
Growth rate of commitment				
Nontightening period	6.3%	3.4%	3.1%	2.6%
2022 tightening cycle	6.8%	2.5%	2.6%	2.3%
Utilization rate of credit lines				
Nontightening period	54.4%	53.4%	53.1%	48.9%
2022 tightening cycle	53.9%	41.9%	41.5%	32.6%
Loan interest rates				
Nontightening period	3.2%	3.4%	3.4%	3.5%
2022 tightening cycle	6.1%	5.4%	5.3%	5.5%

This table reports robustness checks of Figure 4. Using Y-14 loan-level data, loans are classified based on borrower type into BDC borrowers and other borrowers. In Column (2), other borrowers refer to non-BDCs, that is all Y-14 borrowers that are not BDCs. In Column (3), other borrowers refer to primarily non-financial firms, including all Y-14 borrowers that are neither BDCs nor having 3-digit NAICS code 521 (Monetary Authorities-Central Bank) or 522 (Credit Intermediation and Related Activities). In Column (4), other borrowers refer to non-financial firms with good reporting data following Greenwald et al. (2024) and Brown, Gustafson and Ivanov (2021). For each borrower group and quarter, the quarterly growth rate of total loan commitments, the average utilization rate of credit lines, and loan interest rates are computed. The reported values represent the average of these time series across the respective periods.

Table A.2. Firm-Level Summary Statistics

	Count	Mean	SD	Median
Panel A: Overlapping Borrowers				
Total Assets ($ Mn)	11,722	1954	4014	516
EBITDA/Total Asset	11,250	0.09	0.11	0.09
Liquidity	11,250	0.07	0.10	0.03
Interest Coverage	10,972	4.61	8.60	2.42
Tangibility	11,250	0.61	0.30	0.61
Debt/Asset	11,250	0.51	0.28	0.50
Debt/EBITDA	11,248	5.27	8.11	4.66
Sales ($ Mn)	11,279	1319	2874	356
EBITDA ($ Mn)	11,279	279	4358	36.39
Total Debt ($ Mn)	11,279	1630	2830	254
Panel B: Non Overlapping Borrowers				
Total Assets ($ Mn)	722,006	638	3265	16
EBITDA/Total Asset	716,931	0.17	0.20	0.12
Liquidity	716,931	0.12	0.15	0.06
Interest Coverage	663,877	31.80	65.04	8.38
Tangibility	716,931	0.91	0.17	1.00
Debt/Asset	716,931	0.35	0.27	0.30
Debt/EBITDA	718,532	3.04	6.25	1.73
Sales ($ Mn)	722,006	507	2273	31
EBITDA ($ Mn)	722,006	161	21,879	1.8
Total Debt ($ Mn)	722,006	624	4750	3.8

Notes: This table reports firm-level summary statistics of overlapping borrowers (Panel A) and non overlapping borrowers (Panel B). Overlapping borrowers are those that use both bank loans and private credit, and Non Overlapping Borrowers are all other non-financial borrowers. The sample period is 2012–2023, with data at the borrower-year level. The number of unique overlapping borrowers is 4,793. Return on Assets *is the ratio of EBITDA over total assets.* Liquidity *is cash and marketable Securities over total assets.* Interest Coverage *is EBITDA over interest expense amount.* Tangibility *is total tangible assets over total assets.* Debt *is the sum of all short-term debt and long-term debt.* Sales *is reported net sales in a given borrower-year.*

Table A.3. Robustness to Table 3 and Table 5: alternative monetary policy shocks

	Delta Log Loan	Utilization	Interest Rate	LGD	1st Lien	Collateralized
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Monetary Policy Shock from Jarociński and Karadi (2020)						
BDC $\times$ MP Shocks	0.090**	0.573***	0.013	-0.093**	0.282**	0.325**
	(0.038)	(0.200)	(0.013)	(0.041)	(0.135)	(0.133)
BDC	0.005*	0.088***	0.005***	-0.096***	0.314***	0.317***
	(0.003)	(0.018)	(0)	(0.014)	(0.017)	(0.017)
R-squared	0.028	0.286	0.480	0.508	0.265	0.261
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,653,826	1,712,362	3,468,670	3,628,607	3,653,826	3,653,826
Panel B: Monetary Policy Shock from Bauer and Swanson (2023)						
BDC $\times$ MP Shocks	0.047***	0.294**	0.007	-0.043***	0.146*	0.178**
	(0.015)	(0.131)	(0.008)	(0.009)	(0.086)	(0.087)
BDC	0.004*	0.085***	0.005***	-0.095***	0.313***	0.315***
	(0.002)	(0.018)	(0)	(0.014)	(0.017)	(0.017)
R-squared	0.028	0.286	0.480	0.508	0.265	0.261
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,653,826	1,712,362	3,468,670	3,628,607	3,653,826	3,653,826

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports robustness tests for our baseline results in Table 3 and Table 5 using the monetary policy shocks from Jarociński and Karadi (2020) in Panel A and from Bauer and Swanson (2023) in Panel B.

Table A.4. Robustness to Table 6: alternative monetary policy shocks

	Interest Rate	Loan Amount	**1***(Term Loan)
	(1)	(2)	(3)
Panel A: changes in Fed Funds rate ΔFF_t			
$BDC \times \Delta FF_t$	38.935***	14.764***	13.527*
	(8.799)	(5.007)	(7.607)
BDC	1.091***	-0.304***	0.293***
	(0.089)	(0.067)	(0.061)
R-squared 0.932	0.605	0.561	
N	308,962	308,962	471,807
Panel B: Monetary Policy Shock from Jarociński and Karadi (2020)			
$BDC \times MP\ Shock_t$	1.892**	1.692***	1.128*
	(0.765)	(0.440)	(0.593)
BDC	1.173***	-0.281***	0.320***
	(0.097)	(0.062)	(0.055)
R-squared	0.932	0.605	0.561
N	308,962	308,962	471,807
Panel C: Monetary Policy Shock from Bauer and Swanson (2023)			
$BDC \times$ MP Shocks	1.045**	0.836**	0.276
	(0.405)	(0.375)	(0.539)
BDC	1.170***	-0.283***	0.318***
	(0.096)	(0.064)	(0.058)
R-squared	0.932	0.605	0.560
N	308,962	308,962	471,807
Firm x Loan-type x YrQtr FE	Y	Y	N
Firm x YrQtr FE	N	N	Y
Debt Priority FE	Y	Y	Y
Loan Controls	Y	Y	Y

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports robustness tests for results in Table 6 using changes in Fed Funds rate in Panel A, the monetary policy shocks from Jarociński and Karadi (2020) in Panel B, and the monetary policy shocks from Bauer and Swanson (2023) in Panel C.

Table A.5. Robustness to Table 7: alternative monetary policy shocks

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
Jarocinski-Karadi *Shock* × *BankLoanExpense*	1.985***		0.798**	
	(0.668)		(0.353)	
Bauer-Swanson *Shock* × *BankLoanExpense*		0.612		0.448*
		(0.527)		(0.249)
BankLoanExpense	-0.305***	-0.234***	-0.105**	-0.0929**
	(0.0754)	(0.0814)	(0.0431)	(0.0431)
R-squared	0.501	0.501	0.559	0.559
BDC, Yr-Qtr FE	Y	Y	Y	Y
Loan-Type FE	Y	Y	Y	Y
Loan Controls	Y	Y	Y	Y
N	353,559	353,559	341,009	341,009

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports robustness tests for results in Table 7 using the monetary policy shocks from Jarociński and Karadi (2020) and the monetary policy shocks from Bauer and Swanson (2023).

Table A.6. Robustness to Table 3: alternative definitions of other borrowers

	ΔLog Loan	Utilization	Interest Rate	ΔLog Loan	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
BDC × *Tightening*	0.011**	0.141***	0.009***			
	(0.005)	(0.027)	(0.002)			
BDC × ΔFF_t				0.726*	9.450***	0.542***
				(0.409)	(2.111)	(0.114)
BDC	0.001	0.052***	0.002**	0.003	0.079***	0.004***
	(0.003)	(0.019)	(0.001)	(0.003)	(0.017)	(0.001)
R-squared	0.029	0.290	0.480	0.029	0.290	0.480
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,590,663	1,676,659	3,415,275	3,590,663	1,676,659	3,415,275

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table presents robustness checks for Table 3 by restricting the group of non-BDC borrowers to primarily non-financial firms, including all Y-14 borrowers that are neither BDCs nor having 3-digit NAICS code 521 (Monetary Authorities-Central Bank) or 522 (Credit Intermediation and Related Activities).

Table A.7. Robustness to Table 3: utilization rate for all loan types

	Utilization Rate			
	(1)	(2)	(3)	(4)
BDC $\times$ *Tightening*	0.108***	0.089***		
	(0.024)	(0.025)		
BDC $\times$ ΔFF_t			5.803**	5.500**
			(2.687)	(2.171)
BDC	0.012	0.022	0.035*	0.040**
	(0.020)	(0.021)	(0.020)	(0.020)
R-squared	0.475	0.503	0.475	0.503
Bank x Credit Rating FE	Y	N	Y	N
Year FE	Y	N	Y	N
Bank x Credit Rating x YrQtr FE	N	Y	N	Y
Lagged Controls	Y	Y	Y	Y
N	3,653,826	3,653,826	3,653,826	3,653,826

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table presents robustness checks for Columns (2) and (5) of Table 3 by expanding the sample to all loan types.

Table A.8. Robustness to Table 5: restricting sample to existing credit lines

	1st Lien Senior Secured		Collateralized		Loss Given Default		Probability of Default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BDC \times Tightening$	0.107***		0.105***		-0.086***		0.005	
	(0.021)		(0.021)		(0.016)		(0.003)	
$BDC \times \Delta FF_t$		7.235***		6.937***		-5.625***		0.315
		(1.721)		(1.645)		(1.215)		(0.202)
BDC	0.298***	0.318***	0.297***	0.316***	-0.036***	-0.053***	0.001	0.001
	(0.018)	(0.019)	(0.018)	(0.018)	(0.007)	(0.009)	(0.001)	(0.001)
R-squared	0.298	0.298	0.299	0.299	0.496	0.496	0.872	0.872
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	1.53e+06	1.53e+06	1.53e+06	1.53e+06	1.53e+06	1.53e+06	1.53e+06	1.53e+06

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table presents robustness checks for Table 5 by restricting the analysis to credit lines, the predominant lending form for BDCs.

Table A.9. Robustness to Table 3 and Table 5: public and private subsample analysis

	Delta Log Loan	Utilization	Interest Rate	LGD	1st Lien	Collateralized
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Publicly listed BDCs						
BDC $\times$ *Tightening*	0.010*	0.143***	0.009***	-0.011	0.090***	0.086***
	(0.006)	(0.028)	(0.002)	(0.013)	(0.021)	(0.021)
BDC	0.001	0.020	0.002*	-0.096***	0.288***	0.291***
	(0.004)	(0.020)	(0.001)	(0.018)	(0.019)	(0.020)
R-squared	0.028	0.286	0.480	0.508	0.265	0.262
BankxCredit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,652,310	1,710,969	3,467,202	3,627,104	3,652,310	3,652,310
Panel B: Private BDCs						
BDC $\times$ *Tightening*	0.009	0.092**	0.009***	-0.039	0.138***	0.144***
	(0.010)	(0.043)	(0.001)	(0.023)	(0.039)	(0.040)
BDC	0.004	0.127***	0.003***	-0.069***	0.260***	0.261***
	(0.008)	(0.031)	(0.001)	(0.017)	(0.034)	(0.034)
R-squared	0.028	0.287	0.480	0.509	0.266	0.262
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,649,988	1,708,842	3,464,951	3,624,798	3,649,988	3,649,988

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports robustness tests for our baseline results in Table 3 and Table 5 using sub sample analysis for public and private BDC and monetary stance measured using the tightening dummy.

Table A.10. Robustness to Table 3 and Table 5: public and private subsample analysis

	Delta Log Loan	Utilization	Interest Rate	LGD	1st Lien	Collateralized
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Publicly listed BDCs						
$BDC \times \Delta\ FF_t$	-0.219	8.373***	0.527***	-1.201***	4.344***	4.350***
	(0.267)	(2.164)	(0.114)	(0.230)	(1.463)	(1.331)
BDC	0.004	0.043**	0.003***	-0.097***	0.305***	0.306***
	(0.003)	(0.019)	(0.001)	(0.018)	(0.018)	(0.019)
R-squared	0.028	0.286	0.480	0.508	0.265	0.262
BankxCredit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,652,310	1,710,969	3,467,202	3,627,104	3,652,310	3,652,310
Panel B: Private BDCs						
$BDC \times \Delta\ FF_t$	2.283**	9.210***	0.497***	-3.625**	8.872***	9.710***
	(0.942)	(2.544)	(0.117)	(1.415)	(2.673)	(2.661)
BDC	0.003	0.147***	0.006***	-0.078***	0.302***	0.304***
	(0.006)	(0.024)	(0.001)	(0.014)	(0.029)	(0.029)
R-squared	0.028	0.287	0.480	0.509	0.266	0.262
Bank x Credit Rating x YrQtr FE	Y	Y	Y	Y	Y	Y
Lagged Controls	Y	Y	Y	Y	Y	Y
N	3,649,988	1,708,842	3,464,951	3,624,798	3,649,988	3,649,988

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports robustness tests for our baseline results in Table 3 and Table 5 using sub sample analysis for public and private BDC and monetary stance measured using the change in fed funds rates.

Table A.11. Robustness to Table 7: alternative bank reliance measures

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
High Bank Reliant $\times$ *Tightening*	0.197**	0.234***	0.326***	0.285***
	(0.0793)	(0.0781)	(0.0846)	(0.0713)
High Bank Reliant	-0.234***	-0.162**	-0.0274	-0.200***
	(0.0653)	(0.0769)	(0.0636)	(0.0599)
R-squared	0.506	0.506	0.563	0.563
BDC, YrQtr FE	Y	Y	Y	Y
Loan-Type FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
N	363,931	363,931	350,861	350,861

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports robustness tests for Table 7 using alternative measures for BDCs' reliance on banks. For Columns (1) and (3), High Bank Reliant *is a dummy variable equal to 1 if a BDC's utilized bank loan to total debt ratio is in the top quartile (above the 75th percentile) of the sample distribution. For Columns (2) and (4),* High Bank Reliant *is a dummy variable equal to 1 if a BDC's bank loan utilization rate is in the top quartile (above the 75th percentile) of the sample distribution. The rest of the specification is identical to Table 7.*

Table A.12. Robustness to Table 7: alternative controls

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
$Tightening \times BankLoanExpense$	0.380***		0.397***	
	(0.107)		(0.0878)	
$\Delta\ FF_t \times BankLoanExpense$		21.11**		8.498*
		(9.457)		(4.783)
$BankLoanExpense$	-0.328***	-0.140**	-0.411***	-0.205***
	(0.108)	(0.0670)	(0.0984)	(0.0530)
R-squared	0.497	0.497	0.540	0.539
BDC, Yr-Qtr FE	Y	Y	Y	Y
Loan-Type FE	Y	Y	Y	Y
Loan Controls	Y	Y	Y	Y
N	357,815	357,815	344,184	344,184

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table presents robustness checks for Table 7 using an alternative set of controls, including total assets, leverage, bank loan commitment as a share of BDC's total assets, and bank loan commitment as a share of BDC's total debt.