Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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

Sharjil Haque, Young Soo Jang, Jessie Jiaxu Wang

2025-059

Please cite this paper as:
Haque, Sharjil, Young Soo Jang, and Jessie Jiaxu Wang (2025). "Indirect Credit Supply: How Bank Lending to Private Credit Shapes Monetary Policy Transmission," Finance and Economics Discussion Series 2025-059. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2025.059.

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

Sharjil Haque† Young Soo Jang ‡ Jessie Jiaxu Wang §

This Version: July 2025

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 an intermediation chain: Banks lend to Business Development Companies (BDCs)—large private credit providers—which then lend to firms. As monetary tightening restricts bank lending, firms turn to BDCs for credit, prompting BDCs to borrow more from banks. 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, and BDC-dependent firms grow more but exhibit weaker interest coverage ratios. Overall, while bank lending to nonbanks mitigates credit contraction and supports investment during tightening, it amplifies monetary transmission by elevating borrowing costs and financial distress risk.

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

---

*We thank Abhishek Bhardwaj, Matthew Denes, Burton Hollifield, Erica Jiang (discussant), Yueran Ma, Simon Mayer, Phillip Monin, Raghuram Rajan, Irina Stefanescu, seminar participants at the Federal Reserve Board, Virginia Tech, and conference participants at the NBER Summer Institute Corporate Finance meeting, CMU-Pitt-PSU Finance conference for feedback. We also thank Chookaszian Accounting Research Center at Chicago Booth for access to the BDC data, and Joe Yuke, Karl Wirth, and Jewon Shin for research assistance. The views expressed in this paper are those of the authors and do not necessarily represent the views of the Federal Reserve Board or the Federal Reserve System.

†Federal Reserve Board of Governors. Email: sharjil.m.haque@frb.gov.

‡Penn State University. Email: ykj5180@psu.edu.

§Federal Reserve Board of Governors. Email: jessie.wang@frb.gov.

1 Introduction

Bank lending plays a key role in how monetary policy shapes the real economy (Bernanke and Blinder, 1988; Kashyap and Stein, 2000). Typically, banks respond to tighter monetary policy by cutting lending and raising borrowing costs, leading to a contraction in credit supply. However, the financial landscape has evolved, with the rise of nonbank lenders—particularly in private credit—introducing new dynamics into this transmission mechanism. 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. 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 the dynamics of monetary policy transmission through bank-nonbank interactions: (i) like banks, they originate credit to firms, but unlike banks, they do not have access to deposits, and instead partially rely on bank credit lines to finance lending, effectively extending the intermediation chain. (ii) BDCs must disclose detailed portfolio information quarterly, allowing us to merge BDC investment data with regulatory bank loan data and trace the full credit chain. To our knowledge, this is the first paper to study the credit flow 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'

[1] We use 'private credit', 'private debt', and 'direct lending' interchangeably for 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 flexible loan products (Block, Jang, Kaplan and Schulze, 2024; Erel and Inozemtsev, 2022).

[2] BDCs are closed-end investment funds with over \$310 billion in total assets as of 2023, 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

reliance on bank credit has grown significantly, more than doubling after the 2022 monetary tightening cycle compared to pre-2021 levels. Second, nearly 90% of bank lending to BDCs takes the form of credit lines, which are typically larger and offer greater creditor protection than loans to non-BDC borrowers. Finally, the market for bank lending to BDCs appears concentrated.

Examining both banks and BDCs as credit sources, we document the evolution of aggregate credit volume and borrowing costs for nonfinancial businesses during the 2022 monetary tightening cycle.[4] Two key patterns emerge: First, as bank credit to nonfinancial businesses slowed, lending to BDCs accelerated. BDCs maintained high utilization of their bank credit lines and increased lending to nonfinancial businesses, mitigating the aggregate credit supply contraction. Second, banks charged BDCs higher rate premiums, which BDCs passed on to borrowers. Consequently, the weighted average interest rate on combined bank and BDC credit significantly exceeded that of bank credit alone. This dual effect reveals that while BDCs help sustain credit volume during tightening, they simultaneously amplify monetary transmission by increasing borrowing costs for nonfinancial businesses.

To quantify these patterns, we run regressions to estimate how bank loans to BDCs respond to monetary tightening relative to other loans. We control for credit risk using granular internal credit ratings from banks, comparing loans of the same rating, issued by the same bank, at the same time. During the 2022 monetary tightening cycle, banks increased lending to BDCs relative to non-BDC borrowers, with loan commitments to BDCs growing 1.1 percentage points more, and their credit-line utilization rising 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. These findings remain qualitatively robust across various monetary policy measures, includ-

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] We focus on the 2022 cycle due to its unprecedented speed and magnitude of rate hikes and the resulting slowdown in bank credit growth. Unlike the gradual 2015 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.

ing changes in the effective Federal Funds rate and monetary policy shocks identified by Jarociński and Karadi (2020) and Bauer and Swanson (2023). The simultaneous increase in both quantity and price of bank loans to BDC borrowers suggests heightened credit demand from BDCs.

A key channel for banks reallocating credit to BDCs during monetary tightening is the renegotiation of existing credit lines. We find 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 with limit expansions. BDC borrowers also increase credit line drawdowns sharply, particularly on expanded lines. These findings highlight coordination between banks and BDC borrowers: as BDCs draw more from 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.

We find profitability—not risk-taking—drives banks' reallocation of credit to BDCs through two key channels. First, during monetary tightening, BDC loans offer higher returns with lower risk due to greater collateralization, seniority, and lower loss given default. Second, banks may benefit from lower capital requirements on senior collateralized credit facilities to BDCs, enhancing the appeal of BDC lending over direct corporate lending, especially during 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 borrower, quarter, and loan type, we find BDC loans carry a rate premium of nearly 1.5 percentage points during tightening. This premium persists after controlling for borrower risk and loan characteristics including seniority, maturity, and performance. These results suggest that BDCs pass through higher bank funding costs to borrowers, amplifying monetary policy transmission via the price channel. Notably, firms increase BDC credit utilization dur-

[5]For example, banks that use internal estimates for risk-based capital requirements may benefit from lower loss given default on senior secured loans, provided that the underlying collateral meets certain eligibility criteria; see Bank for International Settlements. This benefit arises when the capital requirements calculated under banks' internal models are more binding than those under the standardized approach.

ing tightening, suggesting rising demand for private credit may drive BDCs' increased reliance on bank financing.

Despite higher borrowing costs, firms increase their demand for BDC credit during monetary tightening for two main reasons. First, BDCs absorb residual credit demand left unmet by bank rationing. We find that firms with higher bank loan utilization or shorter bank relationships—proxies for bank borrowing constraint—become significantly more reliant on BDC financing, particularly as monetary policy tightens. Second, BDC loans often include PIK provisions, allowing borrowers to defer interest payments. Such flexibility is especially valuable to borrowers during monetary tightening as the impact of higher rates materializes and credit burdens build up.

We next examine how bank lending to BDCs influences monetary policy transmission along the intermediation chain. Specifically, we test whether BDCs' reliance on bank financing affects their response to monetary tightening, and find that, indeed, more bank-reliant BDCs 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 higher than their less bank-reliant counterparts. This pattern supports a pass-through mechanism: banks pass on higher funding costs to BDCs, who then adjust loan pricing while maintaining or even expanding credit supply.

Finally, we examine how BDCs' credit supply during monetary tightening affects firm-level outcomes, exploring the quantity-price tradeoff. We find that borrowers more reliant on BDC credit exhibit greater capital expenditures and asset growth during monetary tightening, but also experience lower profitability and weaker interest coverage ratios. Additionally, firms that substitute BDC credit for bank debt in 2023 exhibit similar patterns: higher growth but increased leverage and default risk. These findings reveal the real consequences of the private credit intermediation chain: while BDC lending supports firm investments and growth during monetary tightening, it raises financial distress risk through higher borrowing costs.

Taken together, our findings reveal a nuanced impact of bank lending to nonbank lenders during monetary tightening. While this expansion mitigates aggregate contraction in credit supply, it amplifies monetary policy transmission by elevating borrowing costs. This highlights a key tradeoff: private credit dampens the quantity channel by sustaining lending volume, yet intensifies transmission through the price channel. Such tradeoff has important implications on real outcomes of nonfinancial businesses.

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.[6] 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.[7]

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

[6] 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).

[7] 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.

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, 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 utilize the Federal Reserve's administrative matched bank-firm loan-level dataset for bank loan information and Refinitiv's BDC Collateral dataset for BDC financials and investments. These datasets enable us to comprehensively track bank lending to various borrowers, including corporate entities and nonbank lenders like BDCs, 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).[8] This dataset covers detailed information on the universe of bilat-

[8]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 on page 170 in the publicly available reporting form.

eral 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.[9] These reporting 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 (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.[10]

Our analysis primarily relies on quarterly loan-level data and annual borrower-level financials.[11] 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

[9] A loan facility is a lending arrangement between a bank and a borrower that may encompass multiple loans of different types, such as credit lines or term loans. Banks categorize the facility type based on the loan type that represents the majority of the total commitment amount (Greenwald, Krainer and Paul, 2024).

[10] Prior studies have shown that banks' internal credit assessments are highly informative of borrower risk and firm characteristics, and are strong predictors of ex-post default (Weitzner and Howes, 2023; Lee, Li, Meisenzahl and Sicilian, 2019).

[11] Borrower-level financial data are available for approximately 60% of firms in the dataset, with reporting being more frequent among larger firms.

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.

While BDCs invest in debt, equity, and structured products, their portfolios predominantly comprise debt investments. For these debt investments, the BDC collateral dataset provides detailed loan-level information, including borrower details (name and industry), contractual terms (par amount, interest rates, seniority, and loan type), and nonaccrual status. The dataset includes three interest rate measures: all-in yield, cash spread over the base rate, and Payment-in-Kind (PIK) spread—the latter accruing to the loan principal instead of being paid in cash.[12] BDC reports classify three types of loan seniority—first lien, second lien, and subordinated—and provide performance metrics such as fair value and non-accrual status (i.e., whether a loan is nonperforming). To complement this data, we hand-collect unique Taxpayer Identification Number (TIN) for our comprehensive list of BDCs from SEC filings. Our data cleaning and filtration procedures are detailed in Appendix A.3.

Representativeness of BDC Collateral. To assess the representativeness of BDC borrowers in our dataset, we compare key variables across multiple private credit datasets. We reference Jang (2025)'s proprietary database, which covers a significant share of loans extended by both BDCs and private credit funds and is representative of private credit borrowers in PitchBook. As shown in Appendix A.3, our sample aligns with Jang (2025)'s data in terms of the prevalence of first-lien loans and average loan interest rates, suggesting comparable representativeness.[13] Furthermore, our sample's distribution of loan amounts and spreads closely matches other studies, including Davydiuk et al. (2020a), who uses hand-collected data on BDCs, and Haque et al. (2024), who uses Pitchbook data. We find no evidence of systematic differences—particularly in credit risk—between BDC Collateral borrowers and those studied in other private credit research. Given these

[12] 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.

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

similarities, we believe our conclusions from examining BDC data likely extend 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 additional 9 matched using the "Fedmatch" algorithm from Cohen, Dice, Friedrichs, Gupta, Hayes, Kitschelt, Lee, Marsh, Mislang, Shaton et al. (2021), which employs string-matching and probabilistic record linkage methods. This brings the total to 142 BDCs identified as borrowers from banks in the Y-14 data. Our matched sample includes 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.[14]

Matching BDC Borrowers to Y-14. To identify *overlapping borrowers*—firms that simultaneously hold both bank loans and BDC credit—we match BDC borrowers to borrowers in the Y-14 data on a quarterly basis. This matching process utilizes the Cohen et al. (2021) "Fedmatch" algorithm based on borrower name and industry. We then manually verify each match for accuracy.

Monetary Policy Measures. Our primary focus is on the 2022 monetary tightening cycle, notable for its unprecedented speed and magnitude of rate hikes, and the accompanying slowdown in bank credit growth. To measure the stance of U.S. monetary policy, we primarily use two metrics: (1) a dummy variable for the 2022 tightening cycle (2022Q1–2023Q4)—including 2023Q4 despite rate hikes ending in July 2023, as rates remained elevated—and (2) changes in the effective Federal Funds rate.

Recognizing that the Federal Funds rate is endogenous to broader economic conditions affecting both credit demand and supply, we also incorporate monetary policy shocks for robustness. Specifically, we use the shocks identified by Jarociński and Karadi

[14]Our careful examination of nonbank financial intermediaries borrowing from the Y-14 banks confirms that the unmatched BDCs had no outstanding commitments from Y-14 banks during our sample period. Manual verification of SEC credit agreements further reveals that nearly three-quarters of these BDCs have outstanding loans from non-Y-14 banks (e.g., ING Capital or Natixis); some others appear to strategically operate without bank debt, as indicated by names such as "[Redacted] Unlevered Corp BDC."

(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 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). A rapid increase began in 2021 and continued through the 2022 monetary tightening. Total bank loan commitments more than doubled since 2021, surpassing $60 billion. Table 1 reports loan-level summary statistics for key variables in our analysis, distinguishing between loans to BDCs (Panel A) and non-BDCs (Panel B). Below, we highlight several 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 these two groups, a notable nuance emerges when examining the time series. Figure 2 plots the weighted average interest rates of 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.

More than 70% of bank loans to BDCs—and nearly 90% in dollar-weighted terms, as shown in Figure 1—are credit lines.[15] These proportions are significantly higher than for loans to non-BDCs. Credit lines allow borrowers to draw funds up to a precommitted amount at a predetermined spread, enabling them to navigate adverse changes in aggregate lending conditions through unused credit line capacity. Notably, BDCs exhibit higher utilization rates of credit lines compared to non-BDCs reflecting their heavy reliance on credit lines. Bank loans to BDCs tend to have shorter maturities.

Bank loans to BDCs generally offer greater protection to creditors. Examining banks'

[15] Acharya et al. (2024a) also document that banks provide credit lines to nonbanks, but their focus differs from ours, concentrating on REITs and banks' risk exposure to the CRE market.

own ex-ante estimates of loss given default (LGD), we find that the average LGD for BDC loans is about 10 percent lower than for non-BDC loans. This difference likely stems from the fact that BDC loans are more frequently collateralized, with banks holding first-lien, senior secured positions in bankruptcy, as shown in Table 1.

Finally, the market for bank lending to BDCs is highly concentrated, with only a subset of banks engaging in this specialized activity. On average, BDCs maintain borrowing relationships with 5.5 banks. At any given time, slightly over half of the banks in our sample participate in BDC lending. The distribution of this lending is markedly skewed: the top 5 banks account for 63% of the total committed loan amount to BDCs, while the top 10 banks represent about 84%. This level of concentration surpasses that observed in non-BDC lending.

BDC Investments and Financing. Our sample includes all BDCs, which are required to file SEC 10-K/10-Q reports detailing their portfolio holdings. As of 2023Q4, BDCs collectively 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.[16] Table 2 presents 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 flexibility and relationship lending benefits such as the PIK provisions (Block et al., 2024; Jang, 2025). On average, about 9% of borrower-quarters exercise the PIK option to delay interest payments (12.5% weighted by loan amount), with prevalence surging during periods of market stress, such as COVID-19 and the 2022 monetary tightening (Figure 3).

While BDCs utilize both bonds and loans for debt financing, bank funding has been a critical source, and BDCs' reliance on bank funding has grown significantly.[17] Of the 190 BDCs in our sample, 142 borrowed from banks during our sample period and thus

[16] Middle-market firms, with annual sales between \$10 million and \$1 billion, comprise nearly 200,000 U.S. businesses; see here.

[17] The average BDC leverage (Debt/Asset) is 0.4 in our sample. As shown in Figure A.1, leverage has steadily increased, partly driven by the Small Business Credit Availability Act (SBCAA) passed in March 2018 (Balloch and Gonzalez-Uribe, 2021).

appear in the Y-14 data. These bank-reliant BDCs dominate the credit market, providing funding to around 11,500 firms—mostly private entities—and accounting for over 90% of total BDC lending (Appendix Figure A.2).

The increasing dependence on bank funding is evident in several metrics. First, the average ratio of Y-14 bank loan commitments to total debt for BDCs has risen over time, with notable growth during the 2022 monetary tightening cycle (upper panel, Figure 4). Second, interest expenses have become increasingly tied to bank loans, with spikes observed in 2022 during monetary tightening (lower panel, Figure 4). In addition, during the 2022 tightening, average net bank debt issuance was more than twice the magnitude of net equity issuance and almost six times that of net bond issuance (untabulated).[18]

Two factors could explain BDCs' growing reliance on bank funding. First, bank funding, particularly credit lines, offers readily available capital without delay when investment opportunities arise, making it the preferred source of financing for investments.[19] Our untabulated analysis supports this, showing that BDCs' investment elasticity (marginal propensity to invest) with respect to bank debt is 0.995—indicating that BDCs use bank loans almost dollar for dollar to support their investments. This is higher than the elasticity for bonds (0.935) and equity (0.891). Second, the increasing dependence on bank financing across the BDC sector coincides with the rapid growth of private BDCs (Figure A.3). Private BDCs tend to rely more heavily on bank funding, consistent with their higher information asymmetry, necessitating more informationally-sensitive loans from banks (Diamond and Dybvig, 1983; Diamond and Rajan, 2001).

Aggregate Credit Volume and Borrowing Costs for Nonfinancial Businesses. To understand the effect of monetary policy transmission, we examine facts on the aggregate credit volume and borrowing costs for nonfinancial businesses during the 2022 monetary tightening cycle, considering both banks and BDCs as credit sources.

First, while bank credit to nonfinancial businesses slowed and even contracted during

[18] Net debt issuance is current book debt minus lagged book debt, scaled by lagged assets. Net equity issuance is current book equity minus lagged book equity minus current net income, scaled by lagged assets.

[19] In the mortgage market, shadow banks also depend heavily on warehouse credit lines to finance loan originations (Jiang, 2023).

the 2022 tightening, bank lending to BDCs accelerated, suggesting a credit reallocation. BDCs maintained high utilization of their bank credit lines and increased lending to non-financial businesses, boosting aggregate credit volume (upper panel, Figure 5). BDC loan volume during this period nearly tripled compared to pre-2022 levels. This pattern indicates that BDCs' increased borrowing from banks and subsequent lending mitigated the aggregate credit supply contraction during tightening.

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 an average of 6.1% versus 5.4% for non-BDC borrowers—suggesting banks charged a premium to these nonbank lenders (Figure 2). BDCs passing on these higher costs to borrowers amplifies monetary policy transmission. The weighted average interest rate on combined bank and BDC credit carries a significant premium over bank loans alone (lower panel, Figure 5), reaching 1.0% during the 2022 tightening cycle, up from an average of 0.4% pre-2022. Thus, while BDCs mitigate credit supply contraction, they simultaneously amplify monetary transmission by increasing borrowing costs for nonfinancial businesses.

3 Bank Lending to BDCs during Monetary Tightening

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 differed from lending to other borrowers during the 2022 monetary tightening cycle. We examine both the quantity and pricing of bank loans to BDCs relative to other borrowers and uncover the underlying mechanisms driving these differences.

3.1 Regression Framework

We aggregate the quarterly loan-level data into a bank-borrower-quarter panel to capture total credit provision for each borrower-bank pair, as borrowers can have multiple outstanding loans from the same bank. Loan amounts are summed across committed or utilized amounts, while borrowing costs are interest rate averages weighted by utilized amounts.

Our baseline regression model is:

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

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 utilized amounts, and (iv) credit risk measures (seniority in bankruptcy, collateralization, loss given default, and probability of default). The stance of monetary policy (MP_t) is 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 ($X_{i,t-1}$) and fixed effects ($FE_{b,t}$) to account for observed and unobserved heterogeneity, respectively.

Borrower-Level Controls. To account for observable time-varying differences between borrowers, we include lagged borrower-level characteristics ($X_{i,t-1}$) to capture credit risk, bank loan usage, and debt structure. Derived from Y-14 data, these variables include bank-estimated probability of default, expected loss given default, total bank debt, share of term loans in total bank debt, and share of credit lines in total bank debt.

Fixed Effects. We leverage bank-internal credit ratings from Y-14 data, which we refer to as *credit rating*, to compare loans with nearly identical credit risk levels. These ratings are granular, borrower-specific, and bank-dependent, derived from individual banks' internal risk assessment models.[20] As these ratings generally reflect borrower characteristics such as leverage or 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 credit risk and loan outcomes (Weitzner and Howes, 2023; Haque,

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

Mayer and Wang, 2023; Claessens, Ongena and Wang, 2024).

Our specification includes *bank*×*credit rating*×*year-quarter* fixed effects, ensuring comparison of loans made by the same bank, within the same quarter, to BDC and non-BDC borrowers with identical internal credit ratings. These fixed effects account for time-varying lender heterogeneity, such as differences in banks' internal risk assessment models or capital ratios, which can influence lending decisions (Irani, Iyer, Meisenzahl and Peydro, 2021), and by construction, absorb the direct effect of monetary policy (MP_t). We double cluster standard errors at *bank*×*borrower* and *year-quarter* levels, with the sample period spanning 2012Q3–2023Q4.

Coefficient of Interest. Our primary coefficient of interest, β_1, captures the differential response of bank lending to BDC borrowers compared to other borrowers during monetary tightening, in terms of both loan quantity and pricing. We expect β_1 to be positive for loan growth or utilization outcomes if bank lending to BDCs expands during tightening, potentially mitigating broader credit contraction. Similarly, we expect β_1 to be positive for interest rate outcomes if bank lending to BDCs raises borrowing costs during tightening, amplifying monetary policy transmission through the interest rate channel.

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, with no such differences in non-tightening periods. This effect is economically significant, with its magnitude comparable to the sample mean of loan commitment growth for BDCs (Table 1).

Given that most bank loans to BDCs are credit lines, we examine utilization rates in Column (2). 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 in normal periods. This effect is economically large, considering the average credit line utilization rate is around 50%.

Column (3) shows that banks charged BDC borrowers higher interest rates, 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.[21] Our strategy, incorporating lagged borrower credit risk measures (probability of default, expected LGD) as controls and granular bank-internal credit ratings as fixed effects, ensures comparison of loans with nearly identical credit risk levels, ruling out credit risk differences as an explanation for the rate premium.

Columns (4)–(6) confirm these findings using changes in the Fed Funds rate (ΔFF_t) as an alternative policy measure. To address potential endogeneity concerns with monetary policy, we conduct robustness tests using monetary policy shocks from Jarociński and Karadi (2020) and Bauer and Swanson (2023) in Section 6.

Together, these findings indicate that during monetary tightening, banks reallocated credit toward BDCs, indirectly supporting credit supply while raising borrowing costs. The simultaneous increase in both quantity and price of bank credit for BDC borrowers suggests heightened demand from BDCs.

3.3 Renegotiation Through Credit Line Expansions

Credit provision through credit lines involves active decision-making and renegotiation, with banks setting credit limits and borrowers deciding how much to draw. We next investigate whether banks shift credit to BDCs through renegotiation of existing loans or origination of new loans.

In Panel A of Table 4, we separate credit lines into three groups: pre-existing credit lines (Column 1), pre-existing credit lines with limit expansions (Column 2), and newly originated credit lines (Column 3). Our findings indicate that BDC borrowers predomi-

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

nantly 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 for pre-existing credit lines with limit expansions. These patterns hold when using changes in the Fed Funds rate as a measure of monetary policy.[22] 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 BDC borrowers' credit utilization during monetary tightening, focusing on which loan types saw the greatest increase in drawdowns. Panel B of Table 4 examines the growth rate of utilized credit line amounts for all credit lines (Column 1), pre-existing credit lines (Column 2), and pre-existing credit lines with limit expansions (Column 3). 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 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 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 What Drives Banks' Reallocation of Credit to BDCs?

What drives banks' reallocation of credit to BDCs? And does this credit expansion to BDCs, coupled with higher loan rates, reflect increased risk-taking by banks? Our analysis suggests 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

[22] In fact, 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.

exposing banks to additional credit risk. Although 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 significant difference in ex-ante default probabilities compared with loans to other borrowers.

The rate premium with favorable risk profile is consistent with banks' market power in the BDC bank lending market, as documented in Section 2.2. The highly concentrated market for bank lending to BDCs potentially confers upstream market power to banks. The limited number of banks engaged in BDC lending likely contributes to higher costs for BDCs accessing bank credit, similar to the mechanism Jiang (2023) finds in the mortgage market. This specialized market structure enhances banks' ability to balance profitability and risk in their BDC lending portfolios.

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

4 BDC Lending during Monetary Tightening

Having established that banks shift credit to BDCs and charge them higher interest rates during monetary tightening, we now examine 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 if this effect intensifies during monetary tightening. If BDCs face a funding cost premium from banks under contractionary policy, we expect to observe a corresponding premium 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 identify "Overlapping Borrowers"—firms that simultaneously hold both bank loan commitments and BDC credit—by merging Y-14 data with BDC Collateral data. We employ a regression framework similar to Khwaja and Mian (2008) and Chodorow-Reich (2014). Our sample includes about 4,800 overlapping borrowers, with their numbers increasing in recent years, particularly during the 2022 monetary tightening cycle (Figure A.4). Appendix Table A.15 shows that overlapping borrowers tend to be larger, more leveraged, and have lower interest coverage ratios, cash holdings, and tangible assets compared to non-overlapping borrowers. These borrowers predominantly hold credit lines from banks and term loans from BDCs. Since borrowers may increasingly prefer more permanent forms of financing—such as term loans—during periods of tightening, it is important to control for loan type in our analysis.

To test whether BDC loans carry higher interest rates and amounts than bank loans—even within the same borrower, quarter, and loan type—we construct a loan-quarter panel dataset stacking 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 interest rate and loan amount for a given loan l of type z at year-quarter t extended to borrower i. Loan type z includes 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 captures the stance of monetary policy.

We include *borrower×year-quarter×loan type* fixed effects ($FE_{i,t,z}$) to control for time-varying borrower characteristics and systematic differences across loan types. This specification ensures comparison of BDC and bank loans within the same borrower, quarter, and loan type, isolating differences in pricing or amounts from borrower risk and demand variations. Loan-level controls ($X_{l,t}$) include an indicator for non-accruing status, loan maturity, and utilized 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, with a premium of 0.9 percentage points. The positive and statistically significant coefficient on $BDC \times Tightening$ indicates an even higher premium of 1.47 percentage points during monetary tightening. Column (2) further controls for loan seniority with fixed effects for first-lien senior secured, second-lien senior secured, and junior/unsecured debt, with the coefficient on $BDC \times Tightening$ remaining positive, stable, and significant. Given our strict fixed effects, this result cannot be attributed to borrower risk differences, loan type variations, or loan seniority. Overall, our results suggest that BDC lending rates increase more than bank rates during monetary tightening.

Columns (5) and (6) examine loan amounts.[23] We find that firms increase their utilization of BDC loans relative to bank loans during tightening. This suggests rising demand for private credit, prompting BDCs to expand their loan supply and seek additional funding from banks.

Economic Significance The point estimates from Tables 3 and 6 allow us to assess the magnitude of rate amplification along the bank-BDC and BDC-firm segments of the intermediation chain. As noted in Section 3.2, banks charge BDCs an additional 1.1 percentage points in interest during tightening. BDCs, in turn, 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) find that online (fintech) banks charged borrowers 0.4 to 1.5 percentage points more than traditional banks during the 2022 tightening cycle, depending on loan type. Furthermore, as we show in Section 5.2, borrowers heavily reliant on BDC credit experience a 30% lower

[23] We use utilized amounts rather than commitments because BDC collateral reports only utilized amounts, even though Y-14 provides both.

interest coverage ratio during tightening relative to the sample mean.

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 suggests rising demand for private credit during monetary tightening. But why do borrowers demand more BDC loans despite their higher costs? We provide evidence for two potential explanations.

First, some borrowers turn to BDCs because they face constraints in securing additional bank credit, particularly when lending standards tighten.[24] To test this, we re-estimate Eq. (2) by dividing overlapping borrowers into those likely constrained in bank lending and those that are not, based on two measures. The first measure, *borrowing capacity*, considers a borrower-quarter bank loan constrained if the lagged utilization rate of bank loans exceeds the 75th percentile of the sample distribution, indicating nearly exhausted bank borrowing capacity. The second measure, *relationship duration*, deems a borrower-quarter bank loan constrained if the duration of its longest bank relationship is shorter than the sample mean across all bank-borrower pairs, suggesting less benefit from relationship banking (Petersen and Rajan, 1994). Bank loan-constrained borrowers face more difficulty in accessing further bank credit and may have to seek alternative financing at higher costs. The results, presented in Panels B and C of Table 6, show that our findings are more pronounced for bank loan-constrained borrowers, consistent with the bank lending constraints mechanism.

Second, a significant benefit of BDC loans is the option to delay interest payments through PIK provisions. The use of PIK options tend to rise during monetary tightening, as the impact of higher rates materializes and credit burdens build up among borrowers (Figure 3). The flexibility offered by PIK provisions becomes increasingly valuable to borrowers during challenging financial conditions. Supporting this notion, Table 7 shows that borrowers with non-accruing loans are more likely to invoke PIK provisions during

[24] 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.

monetary tightening episodes. This flexibility may explain part of the appeal of BDC loans, despite their typically higher interest rates compared to traditional bank loans.[25] Additional to the above 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 Pass-Through Along the Intermediation Chain

This section examines how bank lending to BDCs influences monetary policy transmission along the intermediation chain. We test whether BDCs' credit supply responses to monetary tightening depend on their reliance on bank funding, and how BDCs' credit supply shapes firm-level outcomes.

5.1 BDCs' Bank Reliance and Monetary Pass-Through

If monetary policy transmits from banks to BDCs and subsequently to firms, we expect more bank-dependent BDCs to exhibit stronger responses to tighter policy. Specifically during the 2022 tightening cycle, we anticipate these BDCs to increase their loan supply while raising borrowing costs, relative to less bank-reliant BDCs.

To test this, we leverage our unique dataset that merges granular Y-14 data on bank loans to BDCs with BDCs' deal-level investment records and their financials. This 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 $BankLoanExpenseShare_{i,t}$, the share of interest payments on bank loan over total interest expenses for BDC i in quarter t. This share has increased over time (Figure 4), with higher values reflecting greater

[25] See this Fitch Ratings article on the rising trends of PIK features in private credit.

reliance on bank credit. We estimate the following model:

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

where $Y_{i,j,t}$ represents BDC (i)-loan (j)-quarter (t) level outcomes, including loan amount and interest rate. MP_t captures the stance of monetary policy. Controls $X_{i,j,t}$ include total BDC assets (to isolate credit supply effects from portfolio expansion), loan maturity, and non-accrual status (to account for credit risk). To address unobservable heterogeneity, we include BDC fixed effects to control for BDC-specific preferences for certain borrower types; year-quarter fixed effects to absorb time-varying macroeconomic conditions that could impact BDC lending; and loan-type fixed effects to account for risk variations across loan structures. Our coefficient of interest is β_1, which measures whether more bank-reliant BDCs exhibit amplified lending responses to monetary policy changes.

Table 8 presents the results. Columns (1)–(2) examine loan amount, while columns (3)–(4) examine interest rate. The coefficient estimate for $BankLoanExpenseShare_{i,t} \times MP_t$ is consistently positive and statistically significant at the 1% level across all columns, suggesting that higher reliance on bank loans is associated with greater loan amounts and higher interest rates during the 2022 monetary tightening.[26]

The estimated effect is economically significant. A BDC with a one-standard-deviation higher *BankLoanExpenseShare* (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 periods. This pattern aligns with a pass-through mechanism: as banks' funding costs rise, they pass them to BDCs, who in turn reprice their loans 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. However, the persistence of BDCs' bank reliance over time suggests that these re-

[26] Across all columns, the coefficient on *BankLoanExpenseShare* 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 bank-dependent BDCs may pursue more conservative lending strategies or favor stable, lower-risk pricing.

lationships 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. Our results remain consistent across all specifications.

In sum, our evidence suggests that BDC funding structure plays a critical role in monetary policy transmission. During the 2022 tightening, more bank-reliant BDCs responded more sharply to policy changes—expanding lending more while charging higher interest rates. These findings underscore the importance of nonbank lenders and their funding structures in shaping monetary policy transmission.

5.2 BDC Credit and Real Effects on Firms

Finally we examine how BDCs' credit supply during monetary tightening shapes firm-level outcomes, exploring the quantity-price tradeoff. Building on our previous findings that private credit dampens the quantity channel by maintaining lending and amplifies monetary tightening through the price channel, we investigate the net effect on firm performance and financial health. We expect firms more dependent on BDCs to invest and grow more rapidly while facing higher interest expenses relative to cash flows, potentially amplifying financial distress.

Firm-Level Regressions We construct an unbalanced firm-year panel using annual borrower-level financials reported in Y-14 data.[27] We measure a borrower's BDC reliance using the ratio of total BDC credit to total firm-level debt and create a *High BDC Reliance* indicator for firms above the sample mean.

Appendix Table A.15 compares overlapping borrowers with high and low BDC re-

[27]To maximize sample size, we relax our definition of overlapping borrowers by including those with BDC credit in year t and bank credit in either year t or $t+1$, as borrowers' financials are typically reported with a lag. Results are robust to alternative constructions, and we provide external validity using another dataset that includes private debt borrowers (with or without bank debt) in Section 6.

liance to non-overlapping borrowers (those in Y-14 that do not hold BDC credit). High-reliance firms are smaller in asset size and more likely to have negative ROA than their low-reliance counterparts, consistent with middle-market firms with negative cash flows depending more on nonbank loans (Chernenko et al., 2022; Haque et al., 2024). Overlapping borrowers generally have fewer tangible assets than non-overlapping borrowers, potentially limiting their access to bank credit.

To understand the real effects at the firm level, we estimate:

$$Y_{i,t} = \alpha + \beta_1(High\ BDC\ Reliance_{i,t} \times MP_t) + \beta_2 High\ BDC\ Reliance_{i,t} + X_{i,t-1} + FE_{j,t} + \epsilon_{i,t}, \tag{4}$$

where $Y_{i,t}$ represents firm(i)-year(t) outcomes: capital expenditure ratio, asset growth, sales growth, ROA, and interest coverage ratio. MP_t captures monetary policy stance. We include lagged firm-level controls $X_{i,t-1}$ to account for observed firm heterogeneity and *3-digit NAICS* $\times$ *Year* fixed effects to absorb time-varying industry-level conditions.

Table 9 reports our results. Firms heavily reliant on BDC credit showed greater capital expenditures during tightening, with the estimated 1.9% difference being economically significant given the 2.0% sample mean (Table A.15). Consistent with this pattern, these firms also exhibited substantially higher asset growth during tightening. We find no significant differences in sales growth, possibly due to lagged effect on sales. However, these firms showed lower profitability, suggesting increased capital investment and asset growth did not immediately boost earnings. Notably, firms heavily reliant on BDC credit experienced a 30% lower interest coverage ratio during tightening relative to the sample mean, implying higher interest expenses and weakening debt service capacity.[28]

These results confirm that the quantity-price tradeoff from private credit provision creates economically meaningful real consequences at the firm level: BDC-reliant borrowers trade off greater investment and asset growth with higher financial distress from more expensive BDC loans.

[28] Unreported tests confirm higher ratios of interest expense to lagged sales during tightening for BDC-reliant borrowers, suggesting the decline in ICR is indeed driven by interest expenses.

Which firms switch from bank to BDC credit? While our firm-level regressions use the *High BDC Reliance* indicator to identify firms heavily reliant on BDC credit, this measure doesn't necessarily capture borrowers actively substituting BDC credit for bank debt during tightening. To examine the real effects of such substitution, we analyze cross-sectional variation in borrowers' debt dynamics from 2022Q4 to 2023Q4, when the effects of monetary tightening are more pronounced. We categorize borrowers into three groups: *Switchers*, who experienced negative growth in bank loan commitments but positive growth in BDC loans; *Credit-Squeezed* borrowers, who saw negative growth in both bank and BDC loans; and *Bank-Favored* borrowers, who experienced bank credit expansion.

Table 10 presents sample means for each group and reveals several key patterns.[29] In terms of size and leverage, *Switchers* are smaller than *Bank-Favored* borrowers but larger than *Credit-Squeezed* borrowers. *Switchers* exhibit higher leverage (Debt/EBITDA of 5.52) compared to *Credit-Squeezed* borrowers (4.69), consistent with increased access to BDC credit. Regarding growth and investment, *Switchers* show substantially higher asset growth (45%) compared to both *Credit-Squeezed* (12%) and *Bank-Favored* (16%) firms, aligning with our earlier findings that BDC-reliant firms invest and grow more rapidly. *Switchers* also exhibit higher sales growth. However, despite this higher growth, *Switchers* show lower ROA (0.07) compared to *Bank-Favored* firms (0.09), suggesting stronger growth did not immediately boost earnings.

Notably, the growth of *Switchers* appears to come with weaker debt service capacity and financial distress risk. They have lower interest coverage ratios (1.65) compared to *Credit-Squeezed* (2.04) and *Bank-Favored* (2.48) firms, consistent with our regression results. Additionally, *Switchers* have higher default probability (0.09) than other groups (0.08 and 0.05) and lower cash holding, indicating that BDCs are funding riskier borrowers.

These patterns reinforce our earlier findings: BDC credit supports firm growth but imposes higher borrowing costs on borrowers during tightening. This growth has not translated into immediate profitability and appears to come with heightened risk of financial distress.

[29]Given the small sample size due to our stringent definitions and focus on a single year, we report descriptive statistics rather than regression results, acknowledging the limitations of this approach.

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 potential endogeneity concerns, 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.1–A.4 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.

Appendix Table A.10 shows 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.

Including Bank-Borrower Fixed Effects. Our baseline specification in Tables 3–5 includes *bank*×*credit rating*×*year-quarter* fixed effects, which effectively ensures 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. These granular fixed effects account for borrower credit risk as well as any time-varying heterogeneity across lenders. However, concerns could still arise regarding the potential endogeneity of the bank-borrower match, where unobserved time-invariant relationships between bank-borrower pairs could drive certain observed differences between BDC loans and non-BDC loans. To alleviate this concern, we check the robustness of our results by additionally incorporating *bank times borrower* fixed effects to strip out unobservable differences across bank-borrower pairs. Appendix Tables A.5–A.6 confirm that our main results remain robust.

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.7 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.8 confirms that, across various specifications, BDC loan utilization remains higher than that of non-BDCs during monetary tightening, supporting our main results.

Second, we extend our analysis in Table 5, which demonstrates lower credit risk for banks on BDC loans, to address potential concerns about loan type heterogeneity. To isolate the effect from differences between credit lines and term loans, we now restrict the analysis to credit lines only. As shown in Appendix Table A.9, our results remain robust under this restriction. Notably, some estimates, particularly for loss given default, become even more pronounced. This analysis strengthens our conclusion that BDCs effectively mitigate banks' credit risk through enhanced collateralization and higher debt priority, enabling them to secure funding even during periods of 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.[30] 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

[30] 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.

for both private and public BDCs, we re-estimate Eq. (1) on split samples. Appendix Tables A.11 (using *Tightening* as the monetary stance measure) and A.12 (using ΔFF_t) present the results. Across specifications, our key findings remain largely consistent for both BDC types. While coefficient estimates in Table A.12 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.

Alternative Controls and Measures for BDCs' Reliance on Banks. In Section 5, we measure a BDC's reliance on bank financing using *BankLoanExpenseShare*, 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.13 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 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, BDC net equity issuance as a share of total assets, bank loan commitment as a share of BDC's total debt, and utilized bank loans as a share of BDC's total debt. These additional controls help account for time-varying characteristics, such as funding structure and bank reliance. For example, including BDC leverage and net equity issuance helps control for fluctuations in equity financing. Appendix Table A.14 confirms that our results remain robust under these alternative specifications.

Robustness with Khwaja-Mian Fixed Effect Specification To ensure that our findings in Section 4.1 based on the Khwaja-Mian triple fixed effect specification are not driven by highly specific variation, we investigate whether the results are robust to a more lenient fixed effects specification. In untabulated results, we confirm that our results hold under borrower $\times$ loan type and time fixed effects. Furthermore, our findings remain unchanged when controlling for fixed vs. floating rate loans, as well as a dummy variable indicating whether the base rate is tied to LIBOR, SOFR, PRIME, or another index. This robustness check helps address potential concerns about the generalizability of our results across different loan characteristics and market conditions.

External Validity of Real Effects: Beyond Overlapping Borrowers Our results in Section 5.2 are based on borrowers holding both bank loans and BDC credit, allowing us to observe their financials in Y-14. To provide external validity, we utilize a proprietary database from Jang (2025) that covers detailed borrower financials and includes loans from both BDCs and other private credit funds. This dataset allows us to assess the generalizability of our findings beyond BDCs and borrowers with bank loans, extending our analysis to a broader spectrum of the private credit market.[31]

We leverage a unique feature of the data that identifies the lead lender for each loan based on actual credit agreements.[32] Private credit-originated loans (lead lender being private credit manager) typically have minimal bank involvement (median bank share of 0%), compared to significant bank participation in bank-originated loans (93%). We use a *PrivateCredit* indicator for borrowers of private credit-originated loans to identify firms exclusively borrowing from private credit managers. These borrowers are substantially smaller, more leveraged, and have fewer tangible assets than Y-14 borrowers (Panel of Table A.16).

Our regression results in Table A.16 shows that firms exclusively borrowing from private credit managers experience stronger growth in assets and sales during the 2022 tight-

[31]This data is sourced from an anonymous third-party valuation firm that provides loan appraisals for private credit managers.

[32]About two-thirds of the loans were originated by private credit managers, with the remainder consisting of bank-originated loans syndicated to them.

ening cycle, with no significant differences in ROA. This aligns with our earlier findings, suggesting that private credit reliance supported firm growth but did not immediately translate into higher profitability.[33]

7 Conclusion

This paper offers new evidence on how banks' financing of nonbank lenders 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 and have important real effects on firms. 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 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 transmission and real outcomes of nonfinancial businesses. 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 pro-

[33]We do not find significant results on capital investments or interest coverage, possibly due to the relatively lower coverage of these variables in the data.

vide 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.

References

Acharya, Viral V, Manasa Gopal, Maximilian Jager, and Sascha Steffen, "Shadow Always Touches the Feet: Implications of Bank Credit Lines to Non-Bank Financial Intermediaries," *Available at SSRN 4847858*, 2024.

_ , Nicola Cetorelli, and Bruce Tuckman, "Where Do Banks End and NBFIs Begin?," Technical Report, National Bureau of Economic Research 2024.

Agarwal, Isha, Malin Hu, Raluca A. Roman, and Keling Zheng, "Lending by Servicing: Monetary Policy Transmission through Shadow Banks," Working Paper 2023.

Albertus, James F and Matthew Denes, "Private equity fund debt: agency costs and cash flow management," *Available at SSRN 3410076*, 2024.

Balloch, Cynthia and Juanita Gonzalez-Uribe, "Leverage Limits in Good and Bad Times," Technical Report, LSE Working Paper 2021.

Bauer, Michael D. and Eric T. Swanson, "A Reassessment of Monetary Policy Surprises and High-Frequency Identification," *NBER Macroeconomics Annual*, 2023, *37*, 87–155.

Becker, Bo and Victoria Ivashina, "Cyclicality of credit supply: Firm level evidence," *Journal of Monetary Economics*, 2014, *62*, 76–93.

Bernanke, Ben S and Alan S Blinder, "Credit, money, and aggregate demand," 1988.

Bernanke, Ben S. and Mark Gertler, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 1995, *9* (4), 27–48.

Bernanke, BenS and Alan S Blinder, "of Monetary Transmission," *The American Economic Review*, 1992, *82* (4), 901–921.

Block, Joern, Young Soo Jang, Steven N Kaplan, and Anna Schulze, "A survey of private debt funds," *Review of Corporate Finance Studies*, 2024, *13* (2), 335–383.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Fintech, regulatory arbitrage, and the rise of shadow banks," *Journal of financial economics*, 2018, *130* (3), 453–483.

Caglio, Cecilia R, R Matthew Darst, and ebnem Kalemli-Özcan, "Risk-taking and monetary policy transmission: Evidence from loans to smes and large firms," Technical Report, National Bureau of Economic Research 2021.

Chernenko, Sergey, Isil Erel, and Robert Prilmeier, "Why do firms borrow directly from nonbanks?," *The Review of Financial Studies*, 2022, *35* (11), 4902–4947.

_ , Robert Ialenti, and David Scharfstein, "Bank Capital and the Growth of Private Credit," Technical Report, Harvard University Working Paper 2024.

Chodorow-Reich, Gabriel, "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *The Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

— **, Olivier Darmouni, Stephan Luck, and Matthew Plosser**, "Bank liquidity provision across the firm size distribution," *Journal of Financial Economics*, 2022, *144* (3), 908–932.

Claessens, Stijn, Steven Ongena, and Teng Wang, "â€ œIf You Don't Know Me by Now... â€ Banksâ€™ Private Information and Relationship Length," Technical Report, CEPR Discussion Papers 2024.

Cohen, Gregory J, Jacob Dice, Melanie Friedrichs, Kamran Gupta, William Hayes, Isabel Kitschelt, Seung Jung Lee, W Blake Marsh, Nathan Mislang, Maya Shaton et al., "The US syndicated loan market: Matching data," *Journal of Financial Research*, 2021, *44* (4), 695–723.

Cucic, Dominic and Denis Gorea, "Nonbank lending and the transmission of monetary policy," Technical Report, Danmarks Nationalbank Working Papers 2024.

Davydiuk, Tetiana, Isil Erel, Wei Jiang, and Tatyana Marchuk, "Common Investors Across the Capital Structure: Private Debt Funds as Dual Holders," Working Paper Fisher College of Business WP No. 2024-21, Fisher College of Business; European Corporate Governance Institute (ECGI) September 30 2024.

— **, Tatyana Marchuk, and Samuel Rosen**, "Direct lenders in the US middle market," *Available at SSRN 3568718*, 2020.

— **, — , and —** , "Market Discipline in the Direct Lending Space," *Available at SSRN 3729530*, 2020.

Degerli, Ahmet and Phillip Monin, "Private Credit Growth and Monetary Policy Transmission," *FEDS Notes*, August 2024.

Denis, David J and Jing Wang, "Debt covenant renegotiations and creditor control rights," *Journal of Financial Economics*, 2014, *113* (3), 348–367.

Diamond, Douglas W and Philip H Dybvig, "Bank runs, deposit insurance, and liquidity," *Journal of political economy*, 1983, *91* (3), 401–419.

— **and Raghuram G Rajan**, "Liquidity risk, liquidity creation, and financial fragility: A theory of banking," *Journal of political Economy*, 2001, *109* (2), 287–327.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, "The deposits channel of monetary policy," *The Quarterly Journal of Economics*, 2017, *132* (4), 1819–1876.

Elliott, David, Ralf Meisenzahl, José-Luis Peydró, and Bryce C Turner, "Nonbanks, banks, and monetary policy: US loan-level evidence since the 1990s," in "Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC" 2019.

— **, Ralf R Meisenzahl, and José-Luis Peydró**, "Nonbank lenders as global shock absorbers: evidence from US monetary policy spillovers," *Journal of International Economics*, 2024, p. 103908.

Erel, Isil and Eduard Inozemtsev, "Evolution of Debt Financing Toward Less Regulated Financial Intermediaries," *Working Paper*, 2022.

—, Jack Liebersohn, Constantine Yannelis, and Samuel Earnest, "Monetary policy transmission through online banks," Technical Report, National Bureau of Economic Research 2023.

Favara, Giovanni, Camelia Minoiu, and Ander Perez-Orive, "Zombie lending to us firms," *Available at SSRN 4065886*, 2022.

Gopal, Manasa and Philipp Schnabl, "The rise of finance companies and fintech lenders in small business lending," *The Review of Financial Studies*, 2022, *35* (11), 4859–4901.

Greenwald, Daniel L, John Krainer, and Pascal Paul, "The credit line channel," *Journal of Finance*, 2024. Forthcoming.

Haque, Sharjil, Simon Mayer, and Irina Stefanescu, "Private Debt versus Bank Debt in Corporate Borrowing," *Available at SSRN 4821158*, 2024.

—, —, and Teng Wang, "How Private Equity Fuels Non-Bank Lending," *Available at SSRN 4429521*, 2023.

Irani, Rustom M, Rajkamal Iyer, Ralf R Meisenzahl, and Jose-Luis Peydro, "The rise of shadow banking: Evidence from capital regulation," *The Review of Financial Studies*, 2021, *34* (5), 2181–2235.

Jang, Young Soo, "Are Direct Lenders More Like Banks or Arm's-Length Investors?," *Working Paper*, 2025.

Jarociński, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, April 2020, *12* (2), 1–43.

Javadekar, Apoorva and Abhishek Bhardwaj, "How does bank lending to non-banks affect credit allocation and systemic risk," *Available at SSRN*, 2024.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Banking without Deposits: Evidence from Shadow Bank Call Reports," Working Paper, National Bureau of Economic Research 2023.

Jiang, Erica Xuewei, "Financing competitors: Shadow banks' funding and mortgage market competition," *The Review of Financial Studies*, 2023, *36* (10), 3861–3905.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, "Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications," *American Economic Review*, 2012, *102* (5), 2301–2326.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, "Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk-Taking?," *Econometrica*, 2014, *82* (2), 463–505.

Kashyap, Anil K and Jeremy C Stein, "What do a million observations on banks say about the transmission of monetary policy?," *American Economic Review*, 2000, *90* (3), 407–428.

Kashyap, Anil K., Jeremy C. Stein, and David W. Wilcox, "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance," *American Economic Review*, 1993, *83* (1), 78–98.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *American Economic Review*, 2008, *98* (4), 1413–1442.

Lee, Seung Jung, Dan Li, Ralf R Meisenzahl, and Martin J Sicilian, "The US Syndicated Term Loan Market: Who holds what and when?," 2019.

Minoiu, Camelia, Rebecca Zarutskie, and Andrei Zlate, "Motivating banks to lend? Credit spillover effects of the Main Street lending program," 2021.

O'Shea, Finian P., Michael C. Brown, and Jordan Wathen, "4Q24 BDC Scorecard: Beyond BDCs; Private Credit Eyes the Interval Fund," 2024.

Petersen, Mitchell and Raghuram Rajan, "The Benefits of Lending Relationships: Evidence from Small Business Data," *Journal of Finance*, 1994, *49* (1), 3–37.

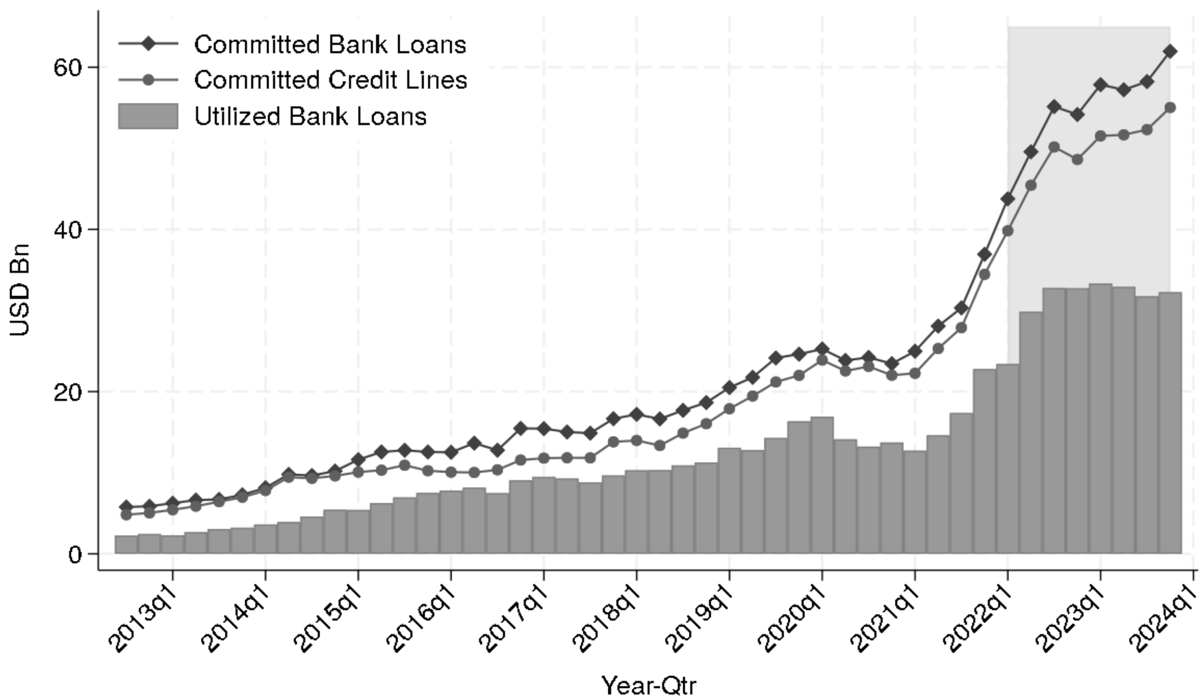
Roberts, Michael R and Amir Sufi, "Renegotiation of financial contracts: Evidence from private credit agreements," *Journal of Financial Economics*, 2009, *93* (2), 159–184.

Turner, David, "Investors are sold on BDC fees, but it's performance that counts," 2019.

Weitzner, Gregory and Cooper Howes, "Bank information production over the business cycle," *Available at SSRN 3934049*, 2023.

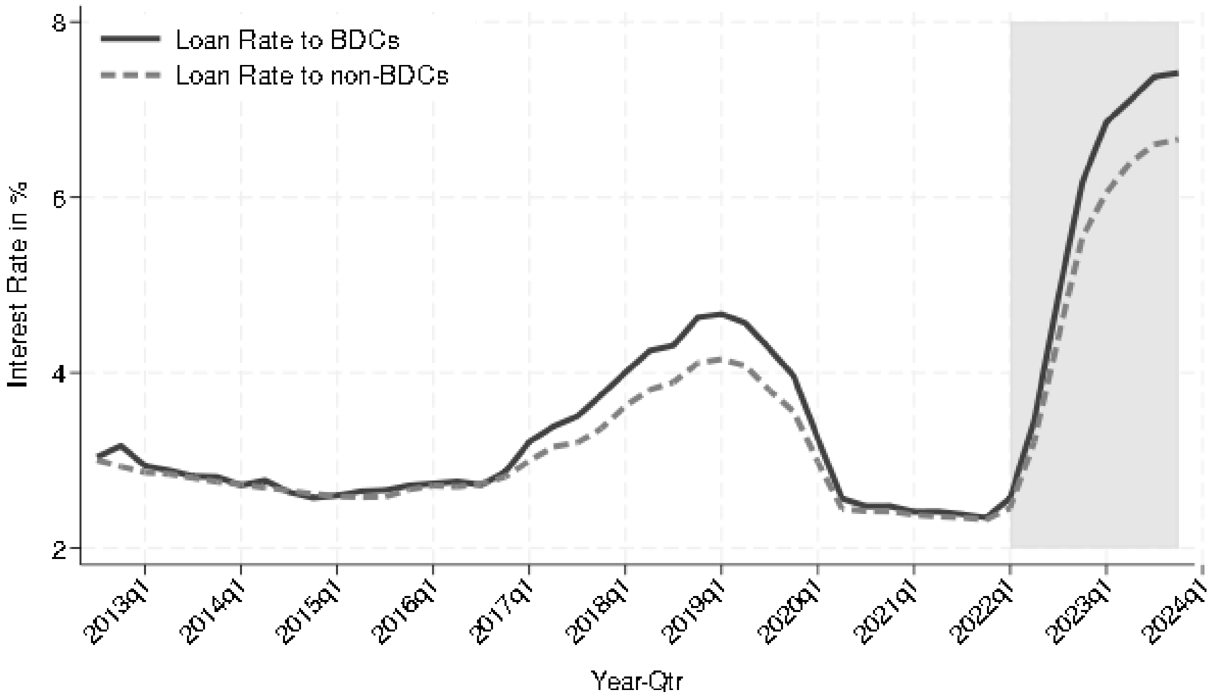
Xiao, Kairong, "Monetary Transmission through Shadow Banks," *The Review of Financial Studies*, 2020, *33* (6), 2379–2420.

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



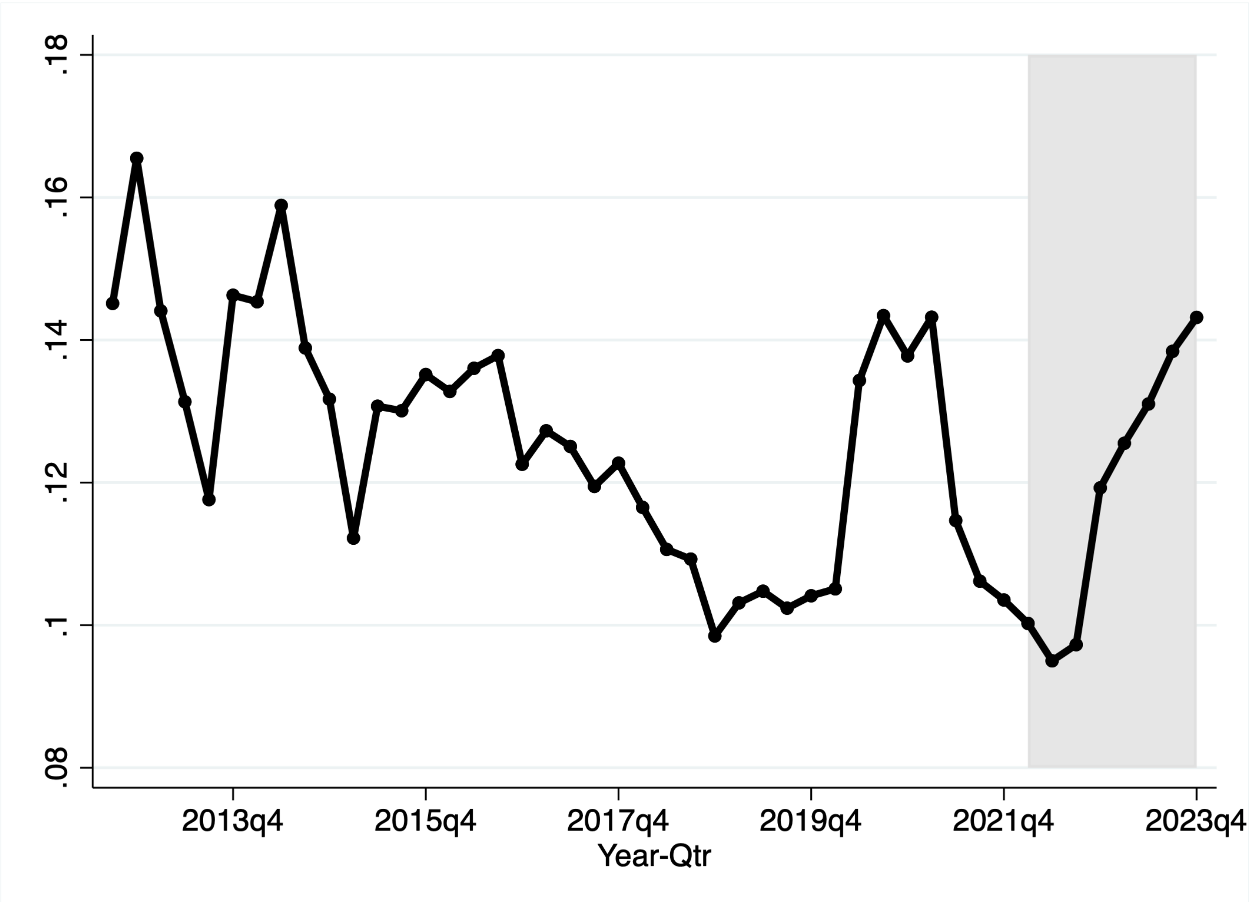
Notes: This figure illustrates the volume and composition of bank lending to BDCs. The dark line with diamond markers represents the aggregate dollar amount of committed bank loans, while the gray line with round markers indicates the aggregate dollar amount of committed bank credit lines. The bars show 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



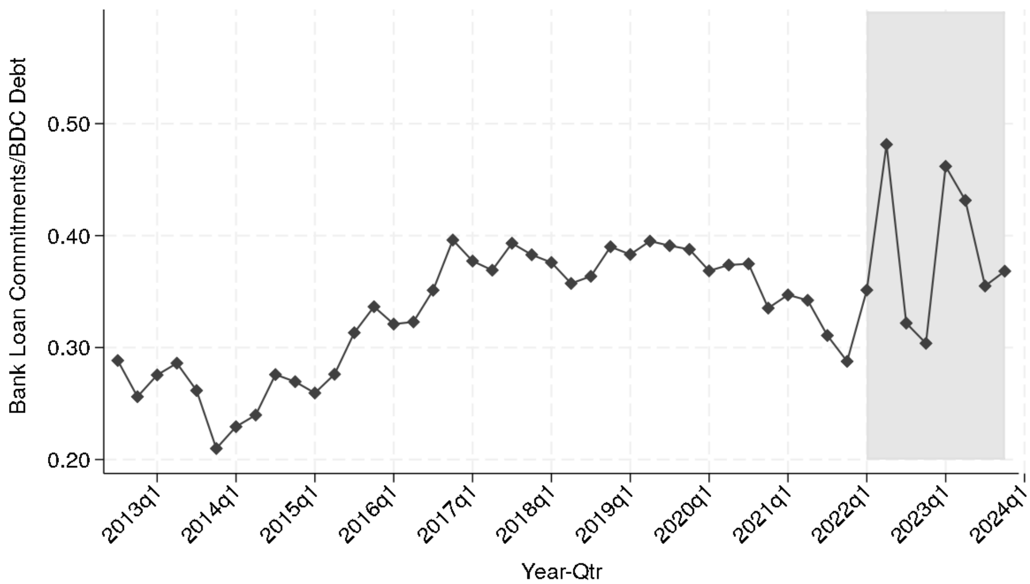
Notes: This figure plots the average time series of interest rates on bank loans to BDC and non-BDC borrowers. Quarterly average interest rates are weighted by the utilized amount, aggregated at the bank-borrower pair level, and expressed in percentage points. Shaded area represents the recent monetary policy tightening cycle (2022Q1–2023Q4). The sample period is 2012Q3–2023Q4.

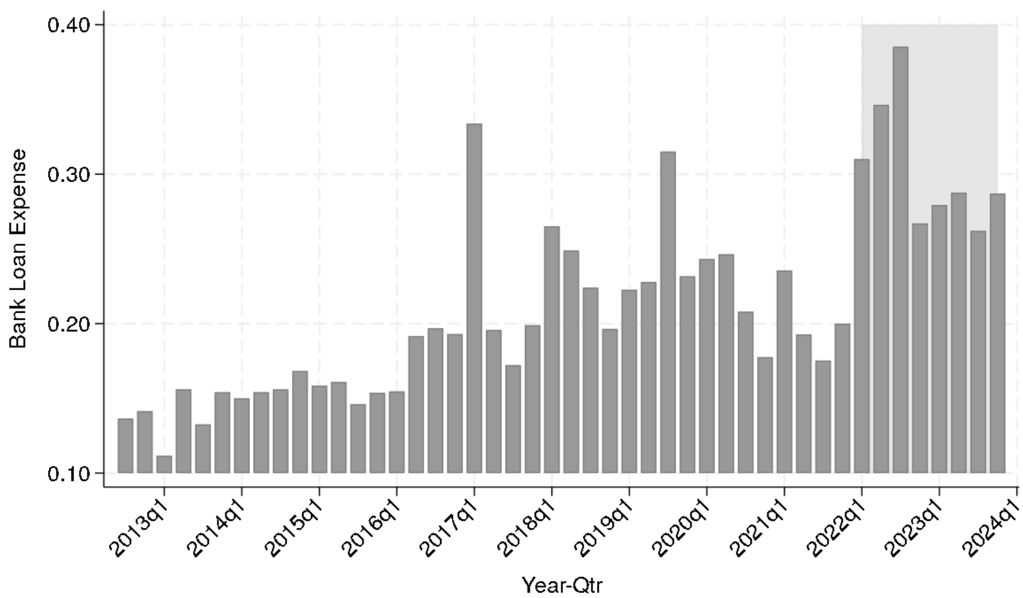
Figure 3. Fraction of BDC loans with PIK spread



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.

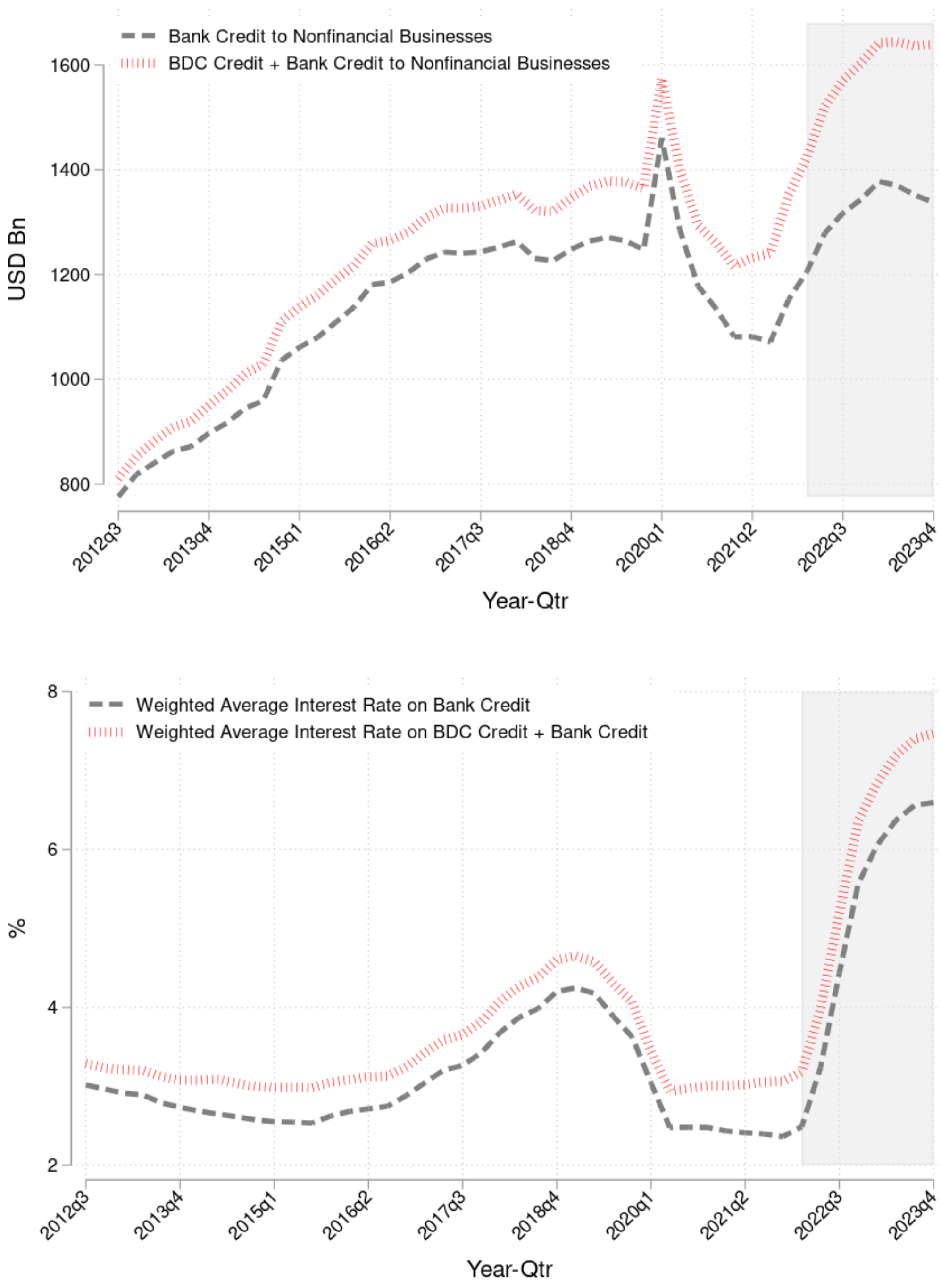
Figure 4. BDCs' Financing: the increasing reliance on banks





Notes: This figure illustrates BDCs' increasing reliance on bank loans. The upper panel plots the average share of bank loan commitments relative to BDC's total debt each quarter. The lower panel plots the average Bank Loan Expense Share—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 5. Aggregate Credit Volume and Borrowing Costs for Nonfinancial Businesses



Notes: This figure illustrates the aggregate credit provision and borrowing costs from banks and BDCs to nonfinancial businesses. The upper panel plots the total utilized bank loans (black dashed line) and the combined total of utilized bank and BDC loans (red dotted line), both expressed in billions of U.S. dollars. The lower panel shows the average interest rates on bank loans and on the combined credit from banks and BDCs, weighted by the utilized amount and expressed in percentage points. Shaded area represents the recent monetary policy tightening cycle (2022Q1–2023Q4). Nonfinancial businesses are defined as borrowers outside the Finance and Insurance sector (i.e., not in 2-digit NAICS code 52). The sample spans 2012Q3–2023Q4 and includes all Y-14 banks and BDCs with matched deal-level information from BDC Collateral.

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
Credit Line Share	10,197	0.72	0.41	0.99
Term Loan Share	10,197	0.02	0.12	0.00
Utilization Rate (only credit lines)	7,970	0.54	0.29	0.54
Maturity (Years)	10,197	5.71	2.53	5.00
$\Delta\ Log(Loan)$	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
Credit Line Share	7,991,557	0.33	0.45	0.00
Term Loan Share	7,991,557	0.31	0.44	0.00
Utilization Rate (only credit lines)	2,941,337	0.50	0.35	0.50
Maturity (Years)	7,056,000	7.57	5.41	5.50
$\Delta\ Log(Loan)$	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.* 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.* Utilization Rate *is the ratio of utilized to committed credit and is defined only for credit lines.*Maturity *is the difference between maturity and origination date in years.* $\Delta\ Log(Loan)$ *is the log change in loan commitment at the bank-borrower level in quarter t from quarter* $t-1$*, expressed in decimal.* First Lien Senior Secured *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).* Loss Given Default *is the expected loan loss rate upon default estimated by the reporting bank.* Probability of Default *is banks' internal estimates of borrower's 1-year ahead probability of default.*

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
$\mathbf{1}\times$ (Borrower Used PIK Option)	442,130	0.09	0.29	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(Borrower Used PIK Option) *is a dummy variable equal to one if a borrower exercises the PIK option for a given loan in a given quarter.* 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)			
$BDC \times \Delta FF$				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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.286	0.480	0.028	0.286	0.480
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-quarter level.* Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF *is changes in the effective federal funds rate. BDC is a 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 bank 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. Standard errors are double clustered at bank × 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)			
$BDC \times \Delta FF$				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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.046	0.256	0.204	0.046	0.256	0.204
Credit Line Sample	Existing	Limit Expanded	New	Existing	Limit Expanded	New
N	1,533,250	295,176	4,993	1,533,250	295,176	4,993

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

Notes: This panel reports regression results from Eq. (1). *The sample period is 2012Q3–2023Q4, with data at the bank-borrower-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 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. 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 Credit Line Utilization	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times Tightening$	0.113*	0.105*	0.266***			
	(0.061)	(0.057)	(0.080)			
$BDC \times \Delta FF$				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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.032	0.035	0.097	0.032	0.035	0.097
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-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 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. All regressions also control for the contemporaneous total bank loan commitment between a given bank-borrower pair. Standard errors are double clustered at bank × 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)
$BDC \times Tightening$	0.103***		0.103***		-0.027**		0.002	
	(0.020)		(0.020)		(0.011)		(0.002)	
$BDC \times \Delta FF$		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)
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.265	0.265	0.261	0.261	0.495	0.495	0.857	0.857
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-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 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BDC \times Tightening$	0.521***	0.516***			0.252***	0.251***		
	(0.116)	(0.117)			(0.093)	(0.077)		
$BDC \times \Delta FF$			37.646***	37.156***			15.094***	14.957***
			(8.238)	(8.342)			(4.978)	(4.945)
BDC	0.949***	0.978***	1.107***	1.135***	-0.378***	-0.372***	-0.294***	-0.288***
	(0.096)	(0.097)	(0.088)	(0.087)	(0.080)	(0.064)	(0.066)	(0.067)
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm × YrQtr × Loan-Type FE	Y	Y	Y	Y	Y	Y	Y	Y
Debt Seniority FE	N	Y	N	Y	N	Y	N	Y
R-squared	0.924	0.924	0.923	0.923	0.604	0.604	0.604	0.604
N	309,692	309,295	309,692	309,295	309,692	309,295	309,692	309,295

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

Notes: This table reports regression results from estimating Eq. (2). The sample period is 2012Q3–2023Q4, with data at the loan-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 6. BDC Loans vs. Bank Loans to Overlapping Borrowers: panel B

Panel B: Splitting Overlapping Borrowers by Bank Lending Constraints Measured by Borrowing Capacity

	Interest Rate				Loan Amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BDC \times Tightening$	0.850***	0.380***			0.319***	0.204*		
	(0.210)	(0.128)			(0.087)	(0.115)		
$BDC \times \Delta FF$			62.668***	23.576***			16.107***	12.960*
			(15.991)	(7.847)			(5.399)	(6.455)
BDC	1.074***	0.896***	1.279***	1.041***	-0.549***	-0.325***	-0.464***	-0.248***
	(0.131)	(0.113)	(0.125)	(0.094)	(0.070)	(0.100)	(0.062)	(0.080)
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm × YrQtr × Loantype FE	Y	Y	Y	Y	Y	Y	Y	Y
Debt Seniority FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.886	0.925	0.885	0.925	0.589	0.604	0.588	0.604
N	34,309	274,986	34,309	274,986	34,309	274,986	34,309	274,986
Bank Loan Constrained	Y	N	Y	N	Y	N	Y	N
H_0 : Constrained - Unconstrained > 0	0.470***		39.092***		0.115**		3.147	

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

Notes: This table presents regression results from estimating Eq. (2) by splitting the sample of overlapping borrowers into those likely facing ex ante bank lending constraints and those that do not. A borrower-quarter is classified as ex ante "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.* H_0 *: Constrained - Unconstrained > 0 is based on a one-tailed test to compare the coefficient differences. Standard errors are double-clustered at the borrower and YearQtr levels.*

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

Panel C: Splitting Overlapping Borrowers by Bank Lending Constraints Measured by Relationship Duration

	Interest Rate				Loan Amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BDC \times Tightening$	0.661***	0.291*			0.263**	0.242**		
	(0.154)	(0.164)			(0.117)	(0.103)		
$BDC \times \Delta FF$			51.413***	14.192			18.411***	9.078
			(10.217)	(10.267)			(6.345)	(5.986)
BDC	0.983***	0.992***	1.171***	1.098***	-0.369***	-0.463***	-0.290***	-0.369***
	(0.115)	(0.153)	(0.100)	(0.131)	(0.096)	(0.087)	(0.076)	(0.083)
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm × YrQtr × Loantype FE	Y	Y	Y	Y	Y	Y	Y	Y
Debt Seniority FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.892	0.928	0.892	0.928	0.604	0.600	0.604	0.600
N	56,066	253,229	56,066	253,229	56,066	253,229	56,066	253,229
Bank Loan Constrained	Y	N	Y	N	Y	N	Y	N
H_0 : Constrained - Unconstrained > 0	0.370**		37.221***		0.021**		9.333**	

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

Notes: This table presents regression results from estimating Eq. (2) by splitting the sample of overlapping borrowers into those likely facing ex ante bank lending constraints and those that do not. A borrower-quarter is classified as "Bank Loan Constrained" if the duration of its longest bank relationship is shorter than the sample mean across all bank-borrower pairs. Bank relationship duration is measured at the borrower-bank-time level as the total number of quarters a given bank-borrower pair has maintained a non-zero loan commitment. For borrowers with multiple lenders, the longest relationship duration among all banks is considered. 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.* H_0 *: Constrained* $-$ *Unconstrained* > 0 *is based on a one-tailed test to compare the coefficient differences. Standard errors are double-clustered at the borrower and YearQtr levels.*

Table 7. Flexibility Benefit of BDC Loans during Tightening: PIK options

	$\mathbf{1}\times$ (Borrower Used PIK Option)			
	(1)	(2)	(3)	(4)
$\mathbf{1}\times$(Nonaccrual Loan) $\times$ *Tightening*	0.120***	0.096**		
	(0.032)	(0.044)		
$\mathbf{1}\times$(Nonaccrual Loan) $\times$ ΔFF			6.694***	5.081*
			(2.046)	(2.552)
$\mathbf{1}\times$(Nonaccrual Loan)	0.127***	0.104***	0.153***	0.142***
	(0.019)	(0.035)	(0.019)	(0.029)
Loan Controls	Y	Y	Y	Y
Firm FE	Y		Y	
Firm $\times$ Loantype FE		Y		Y
YrQtr FE	Y	Y	Y	Y
R-squared	0.574	0.614	0.574	0.614
N	431,981	289,172	431,981	289,172

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

Notes: This table presents evidence on the flexibility benefit of BDC loans during monetary tightening periods, specifically focusing on the option to delay interest payments through Payment-in-Kind (PIK) provisions. The sample comprises all BDC loans from BDC Collateral, spanning from 2012Q3 to 2023Q4, with data at the loan-year-quarter level. The dependent variable, $\mathbf{1}\times$ *(Borrower Used PIK Option), is a dummy variable equal to one if a borrower exercises the PIK option for a given loan in a given quarter.* $\mathbf{1}\times$*(Nonaccrual Loan) in a dummy variable equal to one if the loan is reported as non-accruing in a given quarter.* Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022Q1–2023Q4) and 0 otherwise.* ΔFF *is changes in the effective federal funds rate, expressed as a decimal. Loan Controls include the loan amount, remaining maturity, interest rate and a dummy for fixed rate loans. Standard errors are double-clustered at the borrower and YearQtr levels.*

Table 8. BDCs' Reliance on Bank Financing and Monetary Pass Through

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
$BankLoanExpenseShare \times Tightening$	0.428***		0.313***	
	(0.121)		(0.0735)	
$BankLoanExpenseShare \times \Delta FF$		21.55**		9.056**
		(10.47)		(3.881)
$BankLoanExpenseShare$	-0.442***	-0.247***	-0.231***	-0.0857**
	(0.126)	(0.0879)	(0.0633)	(0.0390)
Controls	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y
R-squared	0.501	0.501	0.559	0.559
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).* BankLoanExpenseShare *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 *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.*

Table 9. Real Effects of BDC Financing during Tightening

	Capex/ Total Assets	Asset Growth	Sales Growth	ROA	Interest Coverage
	(1)	(2)	(3)	(4)	(5)
High BDC Reliance × Tightening	0.019***	0.142***	0.009	-0.042***	-1.840**
	(0.006)	(0.043)	(0.026)	(0.009)	(0.779)
High BDC Reliance	-0.006	-0.125***	-0.032**	0.006	0.454
	(0.004)	(0.021)	(0.015)	(0.005)	(0.338)
Lagged Firm Controls	Y	Y	Y	Y	Y
3-Digit Ind × Year FE	Y	Y	Y	Y	Y
R-squared	0.163	0.182	0.208	0.305	0.263
N	4,810	4,758	4,774	4,860	4,830

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

Notes: This table presents evidence on the real effects of BDC financing on borrowers during monetary tightening by estimating Eq. (4). The sample covers 2012–2023, with data at the borrower-year level. The dependent variable is the ratio of capital expenditures over total assets in column (1), growth rate of total assets over the previous year in column (2), growth rate of sales over the previous year in column (3), ratio of EBITDA to book value of total assets in column (4), and the interest coverage ratio (EBITDA/Interest Expense) in column (5). High BDC Reliance *is a dummy equal to 1 if the borrower's BDC debt/total debt is above sample mean.* Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022–2023) and 0 otherwise. Lagged firm controls include log of total assets, total debt/total assets, ROA, and cash/total assets in columns (1)–(3). ROA is removed as a control variable in columns (4)–(5) as dependent variable includes EBITDA. Industry fixed effects are at the 3-digit NAICS level. Standard errors are clustered at the borrower level.*

Table 10. Firm Characteristics in 2023: Switchers to BDC Credit vs. Others

	Switchers from Bank Credit to BDC Credit	*Credit-Squeezed* by Banks and BDCs	*Bank-Favored*
Total Assets (USD Mn)	3097	2480	3668
Total Debt/EBITDA	5.52	4.69	6.16
Capex/Total Assets	0.00	0.01	0.01
Asset Growth	0.45	0.12	0.16
Sales Growth	0.27	0.13	0.23
ROA	0.07	0.07	0.09
Interest Coverage	1.65	2.04	2.48
Probability of Default	0.09	0.08	0.05
Cash/Assets	0.04	0.06	0.05

Notes: This table presents the sample mean of firm-level characteristics in 2023 for overlapping borrowers, categorized based on changes in their credit composition from 2022Q4 to 2023Q4. Column (1) shows Switchers*, borrowers who experienced negative growth in bank loan commitments but positive growth in BDC loans; Column (2) shows* Credit-Squeezed *borrowers, those who saw negative growth in both bank and BDC loans; and Column (3) shows* Bank-Favored *borrowers, those who experienced bank credit expansion. The sample is limited to one year of overlapping borrowers with valid financial data reported concurrent with loan information in 2023, yielding 91 firms in column (1), 110 firms in column (2), and 243 firms in column (3).*

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-quarter 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.
- Δ $Log(Loan)$: 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-quarter 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-quarter level.
- *Loss Given Default:* Expected loan loss rate upon default estimated by the reporting bank. It is reported as a fraction between 0 and 1.
- *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).
- *Total Debt:* Sum of all short-term debt and long-term debt (USD Mn).
- *Total Debt/Total Assets:* Ratio of total debt to total assets.
- *BDC Debt/Total Debt:* Ratio of BDC debt to Total Debt.
- *High BDC Reliance:* Dummy variable equal to 1 if BDC Debt/Total Debt is above sample mean.
- *Cash/Total Assets:* Ratio of Cash and Marketable Securities to Total Assets, also referred in main text as liquidity.
- *Interest Coverage:* Ratio of EBITDA to interest expense amount.
- *Tangibility:* Ratio of total tangible assets over total assets.
- *Capex/Total Assets:* Ratio of capital expenditures over total assets.
- *Asset Growth:* Growth rate of total assets over the previous year.
- *Sales:* Net sales for the current year (USD Mn).
- *Sales Growth:* Growth rate of sales over the previous year.
- *ROA:* Ratio of EBITDA to book value of total assets, also referred in main text as earnings, or firm profitability.
- $\mathbf{1}\times(ROA < 0)$: Dummy variable equal to 1 if EBITDA/ROA is negative for the current year.
- *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.

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).
- **1**×*(Non-accrual):* Indicator variable equal to 1 if the given loan is reported as non-accruing in a given quarter.
- **1**× (Borrower Used PIK Option): Indicator variable equal to 1 if a borrower exercises the PIK option for a given loan in a given quarter.

BDC-Level Variables.

- *Bank Loan Expense Share:* 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.
- *BDC Net Equity Issuance:* The changes in book equity (NAV) minus current quarter net income scaled by lagged 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.

- Because of timing differences between reported financial information and loan information in the Y-14, the financial data are collapsed at the firm-year level using the year of the *reported financial information* and not the corresponding loan information.

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.

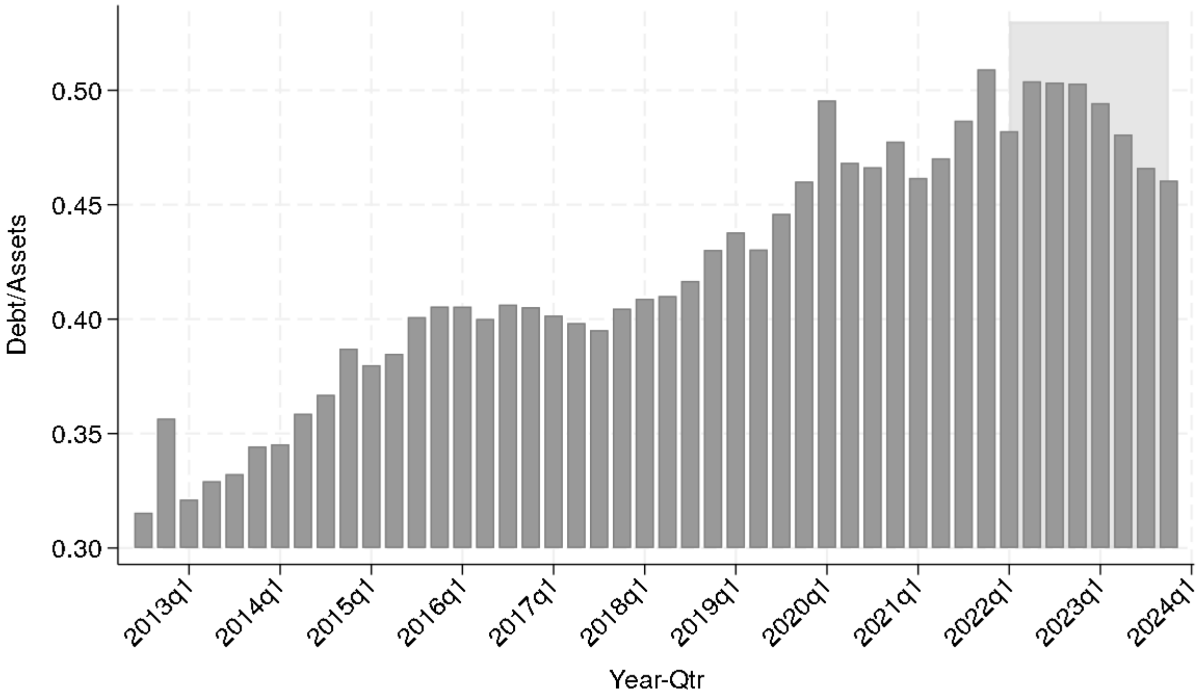
- To evaluate whether BDC borrowers in Refinitiv's BDC Collateral data are representative of the broader private credit market, we perform a balance test comparing key characteristics of BDC borrowers in our sample with private credit borrowers from Jang (2025) over the period 2014Q3–2023Q4. The table 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

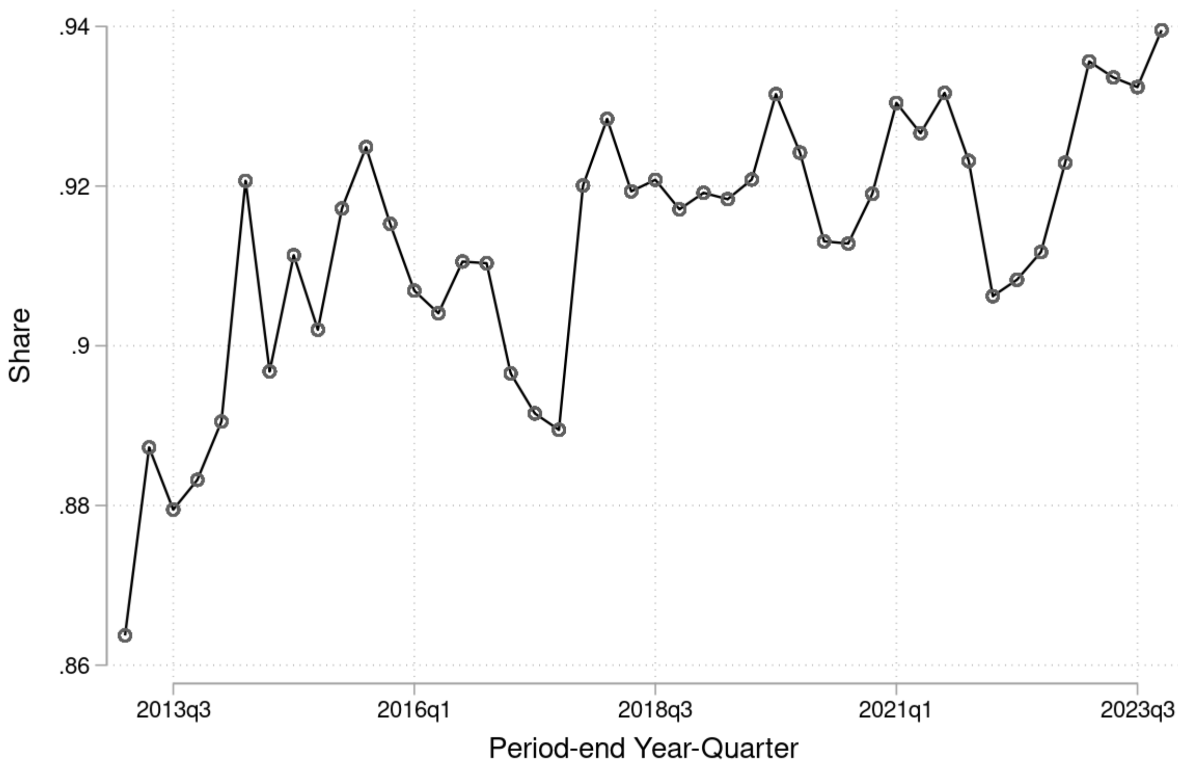
A.4 Additional Figures

Figure A.1. BDC Leverage



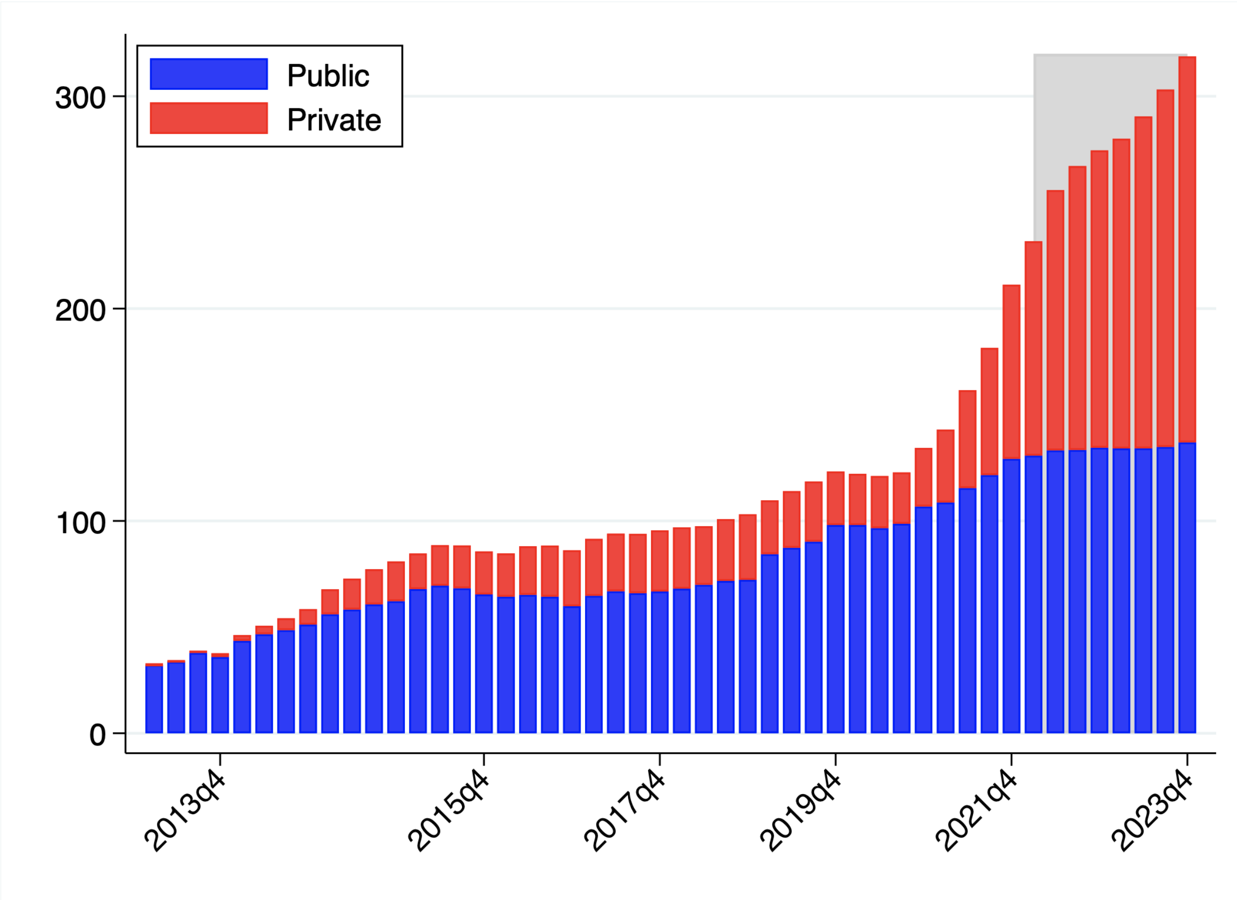
Notes: This figure plots the time series of the average BDC Leverage (Debt/Asset) weighted by BDC assets. The sample period is 2012Q3–2023Q4. The sample includes 190 BDCs with available data.

Figure A.2. Share of BDC Loans Held by Bank-Reliant BDCs



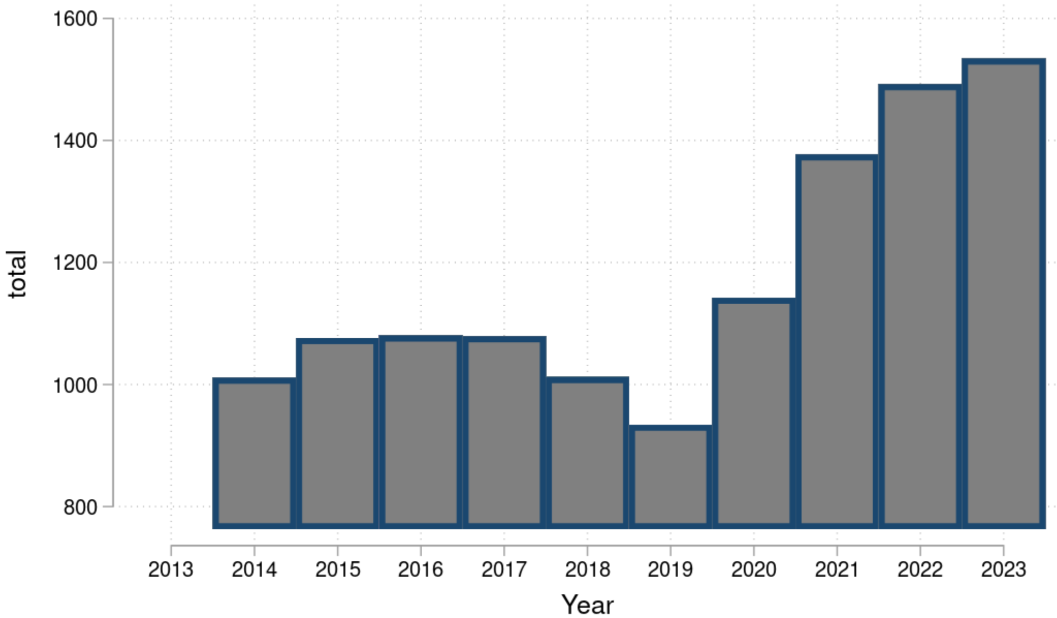
Notes: This figure plots the share of total BDC credit provided by Y-14 bank-reliant BDCs. Credit amount refers to the total par value of loans at a given time for each BDC. Bank-reliant BDCs are those with a non-zero loan commitment from a bank. The sample period spans 2012Q3 to 2023Q4, with 142 unique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

Figure A.3. 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.4. 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.

A.5 Additional Tables

Table A.1. Robustness to Table 3 and Table 5: alternative monetary policy shocks

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

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

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.2. Robustness to Table 6: alternative monetary policy shocks

	Interest Rate	Loan Amount
	(1)	(2)
Panel A: Monetary Policy Shock from Jarociński and Karadi (2020)		
BDC × MP Shock	1.909**	1.687***
	(0.752)	(0.439)
BDC	1.213***	-0.265***
	(0.093)	(0.063)
R-squared	0.923	0.604
N	309,295	309,295
Panel B: Monetary Policy Shock from Bauer and Swanson (2023)		
BDC × MP Shocks	1.059***	0.836**
	(0.389)	(0.369)
BDC	1.209***	-0.267***
	(0.092)	(0.064)
R-squared	0.924	0.604
N	309,295	309,295
Loan Controls	Y	Y
Firm × Loantype × YrQtr FE	Y	Y
Debt Priority FE	Y	Y

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

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

Table A.3. Robustness to Table 7: alternative monetary policy shocks

	$\mathbf{1}\times$ (Borrower Used PIK Option)			
	(1)	(2)	(3)	(4)
$\mathbf{1}\times$(Nonaccrual Loan) $\times$ Jarocinski-Karadi Shock	0.321**	0.193		
	(0.157)	(0.191)		
$\mathbf{1}\times$(Nonaccrual Loan) $\times$ Bauer-Swanson Shock			0.169**	0.136*
			(0.074)	(0.072)
$\mathbf{1}\times$(Nonaccrual Loan)	0.164***	0.151***	0.161***	0.150***
	(0.020)	(0.031)	(0.019)	(0.030)
Loan Controls	Y	Y	Y	Y
Firm FE	Y		Y	
Firm $\times$ Loantype FE		Y		Y
YrQtr FE	Y	Y	Y	Y
R-squared	0.574	0.614	0.574	0.614
N	431,981	289,172	431,981	289,172

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

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.4. Robustness to Table 8: alternative monetary policy shocks

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
BankLoanExpense × Jarocinski-Karadi Shock	1.985***		0.798**	
	(0.668)		(0.353)	
BankLoanExpense × Bauer-Swanson Shock		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)
Loan Controls	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y
R-squared	0.501	0.501	0.559	0.559
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 8 using the monetary policy shocks from Jarociński and Karadi (2020) and the monetary policy shocks from Bauer and Swanson (2023).

Table A.5. Robustness to Table 3: including bank-borrower fixed effects

	ΔLog Loan	Utilization	Interest Rate	ΔLog Loan	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times Tightening$	0.018^{**}	0.089^{***}	0.007^{***}			
	(0.008)	(0.026)	(0.002)			
$BDC \times \Delta FF$				0.552	4.600^{***}	0.325^{***}
				(0.383)	(1.347)	(0.081)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
Bank × Borrower FE	Y	Y	Y	Y	Y	Y
R-squared	0.121	0.744	0.855	0.121	0.744	0.855
N	3,630,073	1,698,343	3,444,201	3,630,073	1,698,343	3,444,201

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

Notes: This table reports robustness tests for our baseline results in Table 3 by including bank-borrower fixed effects.

Table A.6. Robustness to Table 5: including bank-borrower fixed effects

	1st Lien Senior Secured		Collateralized		Loss Given Default		Probability of Default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BDC × *Tightening*	0.039***		0.039***		-0.012**		-0.001	
	(0.014)		(0.013)		(0.005)		(0.001)	
BDC × ΔFF		1.826**		2.150**		-0.672***		-0.026
		(0.815)		(0.915)		(0.238)		(0.081)
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank × Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.882	0.882	0.903	0.903	0.910	0.910	0.915	0.915
N	3,630,073	3,630,073	3,630,073	3,630,073	3,630,073	3,630,073	3,630,073	3,630,073

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

Notes: This table reports robustness tests for our baseline results in Table 5 by including bank-borrower fixed effects.

Table A.7. 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)
$BDC \times Tightening$	0.011**	0.141***	0.009***			
	(0.005)	(0.027)	(0.002)			
$BDC \times \Delta FF$				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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.029	0.290	0.480	0.029	0.290	0.480
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.8. 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			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)
Lagged Controls	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ YrQtr FE	N	Y	N	Y
Bank $\times$ Credit Rating FE	Y	N	Y	N
YrQtr FE	Y	N	Y	N
R-squared	0.475	0.503	0.475	0.503
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 and including alternative fixed effects.

Table A.9. 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 × Tightening	0.107***		0.105***		-0.086***		0.005	
	(0.021)		(0.021)		(0.016)		(0.003)	
BDC × ΔFF		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)
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.298	0.298	0.299	0.299	0.496	0.496	0.872	0.872
N	1,533,250	1,533,250	1,533,250	1,533,250	1,533,250	1,533,250	1,533,250	1,533,250

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

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

Table A.10. The 2015 Tightening Cycle for Table 3 and Table 5

	Delta Log Loan	Utilization	Interest Rate	LGD	1st Lien	Collateralized
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times 2015Tightening$	0.000352	-0.0579*	-0.000112	-0.0252*	-0.0244	-0.0339*
	(0.00693)	(0.0304)	(0.000804)	(0.0125)	(0.0191)	(0.0194)
BDC	0.00358	0.0671***	0.00466***	-0.0837***	0.293***	0.297***
	(0.00396)	(0.0240)	(0.000548)	(0.0142)	(0.0192)	(0.0199)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.029	0.248	0.352	0.488	0.255	0.254
N	2,773,907	1,212,497	2,715,007	2,757,866	2,773,907	2,773,907

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

Notes: This table presents an alternative analysis of our baseline results from Tables 3 and 5. We introduce a new dummy variable, 2015 Tightening*, to capture the tightening cycle that occurred from 2015Q4 to 2018Q4. To isolate the effects of this specific cycle and avoid interference from the 2022 tightening, we restrict our sample period to 2012Q3–2021Q4, ending immediately before the start of the 2022 tightening cycle.*

Table A.11. 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 × *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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.286	0.480	0.508	0.265	0.262
N	3,652,310	1,710,969	3,467,202	3,627,104	3,652,310	3,652,310
Panel B: Private BDCs						
BDC × *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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.287	0.480	0.509	0.266	0.262
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.12. 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						
$BDC \times \Delta FF$	-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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.286	0.480	0.508	0.265	0.262
N	3,652,310	1,710,969	3,467,202	3,627,104	3,652,310	3,652,310
Panel B: Private BDCs						
$BDC \times \Delta FF$	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)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank × Credit Rating × YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.287	0.480	0.509	0.266	0.262
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 subsample analysis for public and private BDC and monetary stance measured by the change in fed funds rates.

Table A.13. Robustness to Table 8: 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)
Controls	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y
R-squared	0.506	0.506	0.563	0.563
N	363,931	363,931	350,861	350,861

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

Notes: This table reports robustness tests for Table 8 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 8.*

Table A.14. Robustness to Table 8: alternative controls

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
$BankLoanExpense \times\ Tightening$	0.313***		0.427***	
	(0.111)		(0.114)	
$BankLoanExpense \times \Delta FF$		21.880**		7.724*
		(8.531)		(3.940)
$BankLoanExpense$	-0.487***	-0.266**	-0.311***	-0.134**
	(0.146)	(0.100)	(0.097)	(0.051)
Controls	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y
R-squared	0.497	0.497	0.537	0.537
N	353,329	353,329	339,846	339,846

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

Notes: This table presents robustness checks for Table 8 using an alternative set of BDC-level controls, including total BDC assets, BDC leverage, BDC net equity issuance (changes in book equity (NAV) minus current quarter net income) as a share of total assets, bank loan commitment as a share of BDC's total debt, and utilized bank loans as a share of BDC's total debt.

Table A.15. Summary Statistics for Borrowers Financials

Variable	Count	Mean	SD	Median
Panel A: Overlapping Borrowers with Low BDC Reliance				
Total Assets (USD Mn)	6,450	2,875	5,537	1,088
Total Debt/Total Assets	6,450	0.58	0.22	0.55
BDC Debt/Total Debt	6,450	0.05	0.06	0.02
Cash/Total Assets	6,450	0.05	0.06	0.03
Interest Coverage	6,424	3.25	5.23	2.32
Tangibility	6,450	0.51	0.28	0.47
Capex/Total Assets	6,386	0.02	0.08	0.01
Asset Growth	3,887	0.14	0.50	0.01
Sales Growth	3,874	0.15	0.42	0.06
ROA	6,450	0.10	0.08	0.09
$\mathbf{1}\times(ROA < 0)$	6,450	0.07	0.25	0.00
Panel B: Overlapping Borrowers with High BDC Reliance				
Total Assets (USD Mn)	2,813	311	912	124
Total Debt/Total Assets	2,809	0.46	0.28	0.44
BDC Debt/Total Debt	2,813	0.60	0.29	0.53
Cash/Total Assets	2,813	0.08	0.11	0.03
Interest Coverage	2,727	5.45	12.87	1.91
Tangibility	2,813	0.54	0.29	0.53
Capex/Total Assets	2,759	0.02	0.07	0.01
Asset Growth	1,570	0.11	0.44	0.00
Sales Growth	1,583	0.12	0.33	0.04
ROA	2,813	0.09	0.11	0.08
$\mathbf{1}\times(ROA < 0)$	2,813	0.19	0.39	0.00
Panel C: Non Overlapping Borrowers				
Total Assets (USD Mn)	722,006	638	3265	16
Total Debt/Total Assets	716,931	0.35	0.27	0.30
Cash/Total Assets	716,931	0.12	0.15	0.06
Interest Coverage	639,113	21.72	40.90	7.82
Tangibility	716,931	0.91	0.17	1.00
Capex/Total Assets	666,364	0.02	0.07	0.00
Asset Growth	530,937	0.48	3.72	0.05
Sales Growth	529,649	0.59	4.89	0.05
ROA	716,931	0.17	0.20	0.12
$\mathbf{1}\times(ROA < 0)$	722,006	0.09	0.29	0.00

Notes: This table presents firm-level summary statistics for three groups of borrowers during 2012–2023, with data at the borrower-year level: Overlapping borrowers with low BDC reliance (BDC Debt/Total Debt below sample mean) in Panel A; Overlapping borrowers with high BDC reliance (BDC Debt/Total Debt above sample mean) in Panel B; Non-overlapping borrowers in Panel C. Overlapping borrowers simultaneously hold both bank loans and private credit. Non-overlapping borrowers are all other non-financial borrowers. The sample includes 3,693 unique overlapping borrowers with available firm financial data.

Table A.16. Real Effects of BDC Credit during Tightening: external validity

Panel A: Summary Statistics

Variable	Count	Mean	SD	Median
Borrowers of Private Credit-Originated Loans				
Total Assets (USD Mn)	4636	357	458	214
Total Debt/Total Assets	4636	0.63	0.31	0.56
Capex/Total Assets	3751	0.02	0.03	0.01
Asset Growth	4636	0.17	0.51	0.00
Sales Growth	4636	0.14	0.29	0.08
ROA	4597	0.10	0.10	0.09
Interest Coverage	3470	2.07	2.62	1.67
Borrowers of Bank-Originated Loans				
Total Assets (USD Mn)	2016	857	978	473
Total Debt/Total Assets	2016	0.65	0.30	0.59
CapEx/Assets	1594	0.02	0.03	0.01
Asset Growth	2016	0.14	0.46	0.00
Sales Growth	2016	0.10	0.25	0.06
ROA	1990	0.10	0.10	0.09
Interest Coverage	1415	2.00	2.58	1.72

Panel B: Regression Results

	Capex/ Total Assets	Asset Growth	Sales Growth	ROA	Interest Coverage
	(1)	(2)	(3)	(4)	(5)
PrivateCredit×	-0.001	0.059**	0.026***	0.008	0.230
Tightening	(0.001)	(0.024)	(0.006)	(0.004)	(0.131)
PrivateCredit	0.000	-0.028**	0.011**	-0.006	-0.228
	(0.001)	(0.012)	(0.005)	(0.006)	(0.139)
Lagged Firm Controls	Yes	Yes	Yes	Yes	Yes
Ind × Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.42	0.12	0.08	0.10	0.05
N	5345	6652	6652	6667	4939

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

Notes: This table presents external validity for Table 9 using a proprietary database from Jang (2025). The sample covers 2014–2023 at the borrower-year level. Panel A provides summary statistics for borrowers of private credit- and bank-originated loans. Panel B presents regression results. Dependent variables follow Table 9. PrivateCredit is a dummy equal to 1 for private credit-originated loans and 0 for bank-originated loans. Tightening *is a dummy equal to 1 for the 2022 monetary tightening (2022–2023) and 0 otherwise. Lagged firm controls include log of total assets, total debt/total assets, ROA, cash/total assets, and Net PP&E/Assets. ROA is excluded as a control in columns (4)-(5) where the dependent variable includes EBITDA. Industry FE are based on the database's classification system: Business Services, Consumer, Energy, Finance, Healthcare, Industrials, TMT (Technology, Media, and Telecommunication), and Others. Standard errors are two-way clustered at the borrower and year level.*