

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

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## Abstract

This paper examines how banks' financing of nonbank lenders affects monetary policy transmission. Using supervisory bank loan-level data and deal-level private credit data, we document 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

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# 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. Direct lending by nonbank lenders has been among the fastest-growing segments of the U.S. financial system, with total assets reaching \$1.1 trillion by 2023, a tenfold increase since 2009.<sup>1</sup> These lenders are increasingly financed by banks, blurring the boundary between the two sectors. 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 that 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 expanding area within the private-credit market that primarily lends to large and middle-market firms.<sup>2</sup> 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 lack deposit funding and instead partly rely on bank credit lines, effectively extending the intermediation chain; and (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 how credit flows from banks to BDCs and ultimately to firms, and to examine its implications for monetary policy transmission.

We begin our analysis using the Federal Reserve’s supervisory Y-14 loan-level dataset, which provides detailed information on bank loans to both private and publicly listed

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<sup>1</sup>We use ‘private credit’ 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; Jang, 2025).

<sup>2</sup>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.

U.S. firms.<sup>3</sup> We document several novel facts about banks' financing of BDCs. First, BDCs' reliance on bank credit has grown sharply, more than doubling after the 2022 monetary tightening cycle compared to pre-2021 levels, as higher bond yields made fixed-rate financing less attractive relative to floating-rate bank loans. On average, bank loans now make up about 40% of BDC debt, up from about 20% a decade ago and close to 50% at its 2022 peak. Second, nearly 90% of bank lending to BDCs is in 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 is fairly 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.<sup>4</sup> 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 expanded lending to nonfinancial businesses, partly offsetting the aggregate credit contraction. Second, banks charged BDCs higher rate premiums, which BDCs passed through to borrowers. Consequently, the weighted average interest rate on combined bank and BDC credit rose much above that of bank credit alone. This dual effect reveals that while BDCs help sustain credit volumes during tightening, they simultaneously amplify monetary transmission by increasing borrowing costs for nonfinancial firms.

To quantify these patterns, we estimate regressions of bank loans to BDCs relative to other loans, controlling for credit risk with granular internal bank ratings and 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: loan commitments to BDCs grew 1.1 percentage points more, and their credit-line utiliza-

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<sup>3</sup>The Y-14 dataset is an administrative, matched bank-firm-loan level dataset collected by the Federal Reserve since 2011 under the Dodd-Frank Act Stress Tests. It offers the richest coverage of U.S. firms with bank loans, including loan characteristics, credit risk metrics, and borrower financials.

<sup>4</sup>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—when 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 firms' reliance on private credit, while liquidity pressures and deposit outflows made secured lending to BDCs more attractive.

tion 18.6 percentage points more. Banks also charged BDCs higher rates, with the interest rate premium reaching 1.1 percentage points. These findings remain qualitatively robust across various monetary policy measures, including changes in the effective federal funds rate and monetary policy shocks identified by [Jarociński and Karadi \(2020\)](#) and [Bauer and Swanson \(2023\)](#). The simultaneous rise in both quantity and price of bank loans to BDCs points to heightened credit demand from BDCs during monetary tightening. Robustness tests further show that these results are not driven by banks' capital or liquidity constraints, reinforcing that the pattern reflects strong credit demand from BDCs rather than bank-side balance-sheet pressures.

A key channel through which banks reallocate credit to BDCs during monetary tightening is renegotiation of existing credit lines. We find that BDC borrowers actively renegotiate for higher commitments, with loan limits rising 4.7 percentage points more than those of other borrowers on expanded credit lines. BDCs also increase drawdowns sharply, particularly on expanded lines. These findings highlight coordination between banks and BDC borrowers: as BDCs draw more on existing credit lines, banks accommodate demand by expanding limits on the most utilized loans, underscoring the role of renegotiation in reallocating credit during monetary contractions.

We find that profitability—rather than risk-taking—drives banks' reallocation of credit to BDCs through two main channels. First, during monetary tightening, loans to BDCs offer higher returns with lower risk due to greater collateralization, seniority, and lower loss given default. The combination of a rate premium and a favorable risk profile is consistent with banks exercising market power in the concentrated BDC lending market, where lending relationships are persistent and switching costs limit competition. Such frictions likely enable banks to charge higher spreads when BDC loan demand rises during tightening. 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.<sup>5</sup>

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<sup>5</sup>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 capital requirements under banks' internal models are more binding than those under the standardized approach.

To examine BDCs' lending strategy during monetary tightening, we focus on overlapping borrowers—firms that hold both bank loans and BDC credit. Roughly two-fifths of private-credit borrowers have relied on banks for financing at some point, underscoring the growing integration between bank and BDC lending. 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 during 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 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 more than their less bank-reliant counterparts. Moreover, BDCs borrowing from banks with higher deposit betas—those facing greater funding-cost sensitivity—raised loan rates more sharply, confirming that funding pressures transmit along the chain. This patterns support a pass-through mechanism: banks pass on higher funding costs to BDCs, who then adjust loan pricing while maintaining or even expanding credit

supply. A back-of-the-envelope calculation shows that a 100-bp policy rate hike translates into roughly a 50-bp increase in private-credit borrowing costs through banks' pricing to BDCs and BDCs' pass-through to their borrowers, with estimates ranging from 40 to 60 bp across specifications.

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, asset growth, and sales growth during monetary tightening, but also experience lower profitability and weaker interest coverage ratios. We also document meaningful lender switching among overlapping borrowers—firms that substitute bank credit with BDC credit during tightening. This substitution is consistent with a genuine elongation of the intermediation chain rather than a mere compositional shift, and these switching firms display 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.<sup>6</sup> 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

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<sup>6</sup>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 \(2017\)](#).

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.<sup>7</sup>

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

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<sup>7</sup>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.



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 variable definitions are included in Appendix A.1.

### 2.1 Data Sources

**Matched Bank-Firm Loan Data from the 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).<sup>8</sup> This dataset covers detailed information on all bilateral and syndicated loan facilities with committed amounts over \$1 million held by Bank Holding Companies (BHCs) subject to the Federal Reserve’s stress tests.<sup>9</sup> These reporting banks hold over 85% of total U.S. banking assets (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 provide a granular view of loan contracts across firms on a quarterly basis. Besides committed and utilized loan amounts, the dataset includes interest rates, spreads, maturity, collateral, bankruptcy priority, ex-ante estimates of loss given default (LGD), and loan-type (e.g., credit line or term loan). The origination date allows us to sep-

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<sup>8</sup>For details on variables contained in schedule H.1 and reporting requirements, see the table beginning on page 170 in the [publicly available reporting form](#).

<sup>9</sup>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 total commitment amount (Greenwald, Krainer and Paul, 2024).



arate new loans from existing ones each quarter. Banks also report annual financial information for borrowers and quarterly internal credit assessments, including credit ratings and default probabilities, which enable us to control for borrower risk and rule out risk-based explanations for interest rate differences between loans to BDCs and non-BDCs.<sup>10</sup>

Our analysis relies on quarterly loan-level data and annual borrower-level financials.<sup>11</sup> Although reporting began in 2011Q3, we start our sample in 2012Q3 when bank coverage stabilized and data structures and variables became consistent. 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 sector representation. Because BDCs must report their holdings to the SEC, the dataset is free of selection bias from missing observations. The dataset also assembles BDCs’ financial data from 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, the dataset provides loan-level details, including borrower name and industry, contractual terms (par amount, interest rate, seniority, loan type), and non-accrual status (whether a loan is nonperforming). The dataset includes three interest rate measures: all-in yield, cash spread over base rate, and payment-in-kind (PIK) spread—the latter accruing to principal instead of being paid in cash.<sup>12</sup> BDCs classify loans by seniority—first lien, second lien, and subordinated—and report performance metrics such as fair value and non-accrual status. To complement this data, we hand-collect unique Taxpayer Identification Number (TIN) for our comprehensive list of BDCs from SEC filings. Appendix A.3 details the cleaning and filtration procedures.

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<sup>10</sup>Prior studies show that banks’ internal credit assessments are highly informative about borrower risk and are strong predictors of ex-post default (Weitzner and Howes, 2023; Lee, Li, Meisenzahl and Sicilian, 2019).

<sup>11</sup>Borrower financials are available for roughly 60% of firms, with higher coverage among larger borrowers.

<sup>12</sup>Unlike the Y-14 data, BDC Collateral does not contain financial information for BDCs’ borrowers (investees), as BDCs are not required by the SEC to disclose such details.

**Representativeness of BDC Collateral.** To assess sample representativeness of BDCs, we compare key variables with other private credit datasets. We reference [Jang \(2025\)](#)’s proprietary database, which covers a large share of loans 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 the prevalence of first-lien loans and average loan rates, suggesting comparable coverage.<sup>13</sup> Furthermore, our distribution of loan amounts and spreads closely matches other studies, including [Davydiuk et al. \(2020a\)](#), who uses hand-collected data on BDCs, [Chernenko et al. \(2024\)](#) who use S&P LCD, and [Haque et al. \(2024\)](#), who use Pitchbook. We find no evidence of systematic differences—particularly in credit risk—between BDC Collateral borrowers and those in other private credit studies. Hence, results based on BDC Collateral are likely representative of the broader private-credit market.<sup>14</sup>

**Matching BDCs to Y-14.** We match BDCs borrowing directly from banks to Y-14 primarily using their TINs. This identifies 133 BDCs, with an additional 9 matched using the “Fedmatch” algorithm of [Cohen, Dice, Friedrichs, Gupta, Hayes, Kitschelt, Lee, Marsh, Mislang, Shaton et al. \(2021\)](#), which employs string-matching and probabilistic record linkage methods. In total, we identify 142 BDCs as Y-14 bank borrowers. 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 terms.<sup>15</sup>

**Matching BDC Borrowers to Y-14.** To identify *overlapping borrowers*—firms that simultaneously obtain credit from both banks and BDCs—we match BDC borrowers to Y-14

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<sup>13</sup>Loan type and interest rate are the only directly comparable variables across datasets. Since both rely on investor holdings data rather than issuance data, loan-maturity coverage is limited.

<sup>14</sup>Our conversations with large asset managers reveal that it is common to split a loan commitment across multiple vehicles on a pro-rata basis, including a BDC and a private credit fund. Thus, BDCs serve as a reliable representation of the broader private credit market.

<sup>15</sup>Manual review confirms that 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.”

borrowers 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. Roughly 39% of BDC borrowers appear in the Y-14 data at some point, and about 4,800 firms hold both bank and BDC credit in the same quarter, indicating substantial overlap between the two lending markets.

**Monetary Policy Measures.** Our main focus is 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 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 shocks from [Jarociński and Karadi \(2020\)](#), which isolate unexpected monetary policy shifts using high-frequency changes in short-term interest rate derivatives around FOMC announcements. Additionally, we employ an updated version of the [Bauer and Swanson \(2023\)](#) measure, which similarly captures unexpected policy changes during FOMC meetings.

## 2.2 Empirical Facts

**Bank Lending to BDCs.** Bank lending to BDCs saw steady growth through most of the sample period (Figure 1). A rapid increase began in 2021 and continued through the 2022 monetary tightening. Since 2021, total bank loan commitments more than doubled, 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 lending 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 seven and fourteen times, respectively, the size of the loans to non-BDCs.

A similar pattern holds for utilized loan amounts. While average interest rates are comparable across these two groups, Figure 2 shows that weighted average rates on BDC loans tend to rise more during monetary tightening. Thus, BDC loans generally carry higher rates relative to non-BDC loans when monetary policy tightens.

More than 70% of bank loans to BDCs—and nearly 90% in dollar-weighted terms, as shown in Figure 1—are credit lines.<sup>16</sup> These proportions are considerably 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 than non-BDCs, reflecting their greater reliance on credit lines. Bank loans to BDCs also tend to have shorter maturities.

Bank loans to BDCs offer greater protection to creditors. Examining banks' 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 active in this specialized activity. On average, BDCs maintain borrowing relationships with about 5.5 banks, and slightly more than half of the banks in our sample participate in BDC lending at any given time.<sup>17</sup> The distribution of loan commitments is markedly skewed: the top five banks account for 63% of total committed amounts to BDCs, and the top ten for about 84%—a substantially higher concentration than in non-BDC lending. This concentration suggests that a limited number of banks may exert significant market power over BDC borrowers.

Consistent with market power, we find strong evidence of persistent bank-BDC re-

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<sup>16</sup>Acharya et al. (2024a) also document that banks extend credit lines to nonbanks, but their focus differs from ours, concentrating on REITs and banks' risk exposure to the CRE market.

<sup>17</sup>Roughly 60% of credit lines to BDCs in the Y-14 data are syndicated. Although the exact number of participating banks per syndicate is unobservable, the typical syndicate size is about 5 banks—consistent with the average number of bank relationships per BDC and with Blickle, Fleckenstein, Hillenbrand and Saunders (2022), who find that syndicated credit lines are generally funded by 4–6 banks. These patterns suggest that BDCs likely rely on a small, stable group of banks to provide large syndicated credit lines, making it costly to replace or restructure an existing syndicate.

relationships following the methodology of [Jiang \(2023\)](#). Appendix Figure [A.1](#) shows that these relationships display high persistence: even after fifteen quarters, a BDC has roughly a 35% probability of borrowing from the same bank, comparable to or even slightly higher than the persistence observed for nonfinancial firms. This persistence indicates that BDCs face nontrivial switching costs when replacing bank lenders, reflecting informational frictions and relationship-specific capital. Together, the high market concentration and the durability of relationships point to limited competition and meaningful frictions in the BDC funding market. These frictions likely enable banks to extract rents from loan demand surges—such as during monetary tightening—by charging higher rates.<sup>18</sup>

**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. They primarily lend to middle-market firms, which account for one-third of private-sector GDP.<sup>19</sup> 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 stress such as COVID-19 and the 2022 monetary tightening (Figure [3](#)).

While BDCs utilize both bonds and loans for debt financing, bank funding remains a critical source, and BDCs’ reliance on it has grown significantly.<sup>20</sup> Of the 190 BDCs in our sample, 142 borrowed from banks during our sample period and thus appear in the Y-14 data. These bank-reliant BDCs dominate the market, funding around 11,500 firms—

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<sup>18</sup>See [Jiang \(2023\)](#) for evidence of persistent warehouse-lending relationships in mortgage market that create switching costs for shadow banks.

<sup>19</sup>Middle-market firms, with annual sales between \$10 million and \$1 billion, comprise nearly 200,000 U.S. businesses; see [here](#).

<sup>20</sup>The average BDC leverage (Debt/Asset) in our sample is 0.4. As shown in Figure [A.2](#), leverage has steadily increased, partly due to the Small Business Credit Availability Act (SBCAA) of March 2018 ([Balloch and Gonzalez-Urbe, 2021](#)).

mostly private—accounting for over 90% of total BDC lending (Appendix Figure A.3).

The increasing dependence on bank funding is evident across several metrics. First, the average ratio of Y-14 bank loan commitments to total debt among BDCs has risen steadily over time, with a pronounced jump during the 2022 monetary-tightening cycle (upper panel, Figure 4). At the same time, bond financing slowed sharply as bond yields rose—from roughly 3% before the tightening cycle to over 8% by end-2023—making fixed-rate issuance less attractive than floating-rate bank loans. From Mergent FISD, BDC bond issuance declined markedly during this period, underscoring banks’ growing importance as a funding source as BDCs expanded their lending activities.<sup>21</sup> During the 2022 tightening, average net bank-debt issuance exceeded net equity issuance by more than twofold and net bond issuance by nearly sixfold (untabulated).<sup>22</sup> Second, interest expenses became increasingly tied to bank loans, with visible spikes in 2022 as policy rates rose (lower panel, Figure 4).

Two factors help explain BDCs’ growing reliance on bank funding. First, bank credit, particularly in the form of credit lines, provides readily available capital when investment opportunities arise, making it the preferred financing source for new investments.<sup>23</sup> Our untabulated analysis supports this view: the 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 fund investments—higher than the corresponding elasticities for bonds (0.935) and equity (0.891). Second, the rising dependence on bank financing coincides with the rapid growth of private BDCs (Figure A.4). Private BDCs rely more heavily on bank funding, consistent with their higher information asymmetry and greater need for informationally sensitive lending relationships with banks (Diamond and Dybvig, 1983; Diamond and Rajan, 2001).

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<sup>21</sup>BDC bond issuance rose through 2021 but contracted sharply after mid-2022. More than half of 2022 issuance came from the Blackstone Private Credit Fund, mainly via shorter-maturity bonds. BDC bonds are typically long-term, with about 54% having maturities of five years or more; 39 BDCs issued such bonds during 2020–2021 compared to only 21 BDCs during 2022–2023.

<sup>22</sup>Net debt issuance equals current book debt minus lagged book debt, scaled by lagged assets. Net equity issuance equals current book equity minus lagged book equity minus current net income, scaled by lagged assets.

<sup>23</sup>In the mortgage market, shadow banks similarly depend on warehouse credit lines to finance loan originations (Jiang, 2023).

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

First, as bank credit to nonfinancial businesses slowed and even contracted during the 2022 tightening, bank lending to BDCs accelerated, suggesting a reallocation of credit. BDCs maintained high utilization of their bank credit lines and expanded lending to nonfinancial firms, boosting aggregate credit volume (upper panel, Figure 5). During this period, BDC loan volumes nearly tripled relative to pre-2022 levels. This pattern indicates that increased borrowing by BDCs and their subsequent lending activity helped offset part of the aggregate credit supply contraction during monetary tightening.

Second, while interest rates on BDC and non-BDC loans were comparable before the tightening, rates on BDC loans rose more sharply during the 2022 cycle—to an average of 6.1% versus 5.4% for non-BDC borrowers—suggesting that banks charged a premium to nonbank lenders (Figure 2). Because BDCs pass through these higher funding costs to their own borrowers, this mechanism amplifies monetary policy transmission. The weighted-average interest rate on combined bank-and-BDC credit carried a significant premium over bank loans alone (lower panel, Figure 5), reaching 1.0% during the 2022 tightening, up from 0.4% pre-2022. Thus, while BDCs helped mitigate the contraction in credit supply, they simultaneously intensified monetary transmission by raising 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 quarterly loan-level data into a bank-borrower-quarter panel to capture total credit provision for each borrower-bank pair, as borrowers may have multiple loans from the same bank. Loan commitments and utilizations are summed across loans, while borrowing costs are utilization-weighted interest rate averages.

Our baseline regression model is:

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

where  $Y_{i,b,t}$  denotes borrower ( $i$ )-bank ( $b$ )-quarter ( $t$ ) outcomes, including: (i) quarterly growth rate of loan commitments, (ii) credit line utilization rate, (iii) interest rate weighted by utilized amounts, and (iv) credit risk measures (seniority in bankruptcy, collateralization, loss given default, and probability of default). Monetary policy stance ( $MP_t$ ) is captured by a dummy for the 2022 tightening cycle ( $Tightening_t$ ) and by changes in the effective federal funds rate ( $\Delta FF_t$ ).  $BDC_i$  is a borrower-level indicator for BDCs. We include lagged borrower characteristics ( $X_{i,t-1}$ ) and bank-time fixed effects ( $FE_{b,t}$ ) to control for observable and unobservable heterogeneity.

**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.<sup>24</sup> As these ratings generally reflect borrower characteristics such as leverage or size and are updated over time—where poor loan performance

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<sup>24</sup>Banks in our sample typically have 10 to 15 rating buckets, though some employ even more detailed credit rating classifications.

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

Our specification includes  $bank \times credit\ rating \times year\text{-}quarter$  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  $bank \times borrower$  and  $year\text{-}quarter$  levels, with the sample period spanning 2012Q3–2023Q4.

**Coefficient of Interest.** Our primary coefficient of interest,  $\beta_1$ , 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  $\beta_1$  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  $\beta_1$  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.<sup>25</sup> 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 ( $\Delta FF_t$ ) as an alternative policy measure. A 100-bp increase in the federal funds rate is associated with roughly a 53-bp higher interest rate on bank loans to BDCs relative to other borrowers. 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. Since BDCs rely more on credit lines than other borrowers, one concern is that our results may reflect differences in loan types. Section 6 shows that our findings remain robust when controlling for  $CreditLine \times MP$  and when restricting to credit lines only.

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. To further assess whether the observed increase in both the quantity and price of bank credit to BDCs reflects heightened demand rather than bank-driven supply conditions, we test the sensitivity of our results to banks' finan-

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<sup>25</sup>By 2023Q4, total utilized bank loans by BDCs reached \$27.24 billion, with total bank loan expenses of \$2.05 billion.

cial constraints. Following the spirit of [Kashyap and Stein \(2000\)](#), we examine whether capital or liquidity constraints among banks can explain the reallocation of credit toward BDCs. We classify banks as financially constrained each quarter using two standard measures based on their capital ratios and liquid-asset holdings (available-for-sale securities relative to risk-weighted assets).<sup>26</sup>

Results in Appendix Table [A.1](#) show that excluding financially constrained banks leaves our findings unchanged. Loan commitments and utilization by BDC borrowers continue to rise more sharply than those of other borrowers during the 2022 tightening, and banks still charge higher rates to BDCs. Even among constrained banks, loan rates to BDCs remain higher (untabulated), indicating that these banks are not paying a premium for the relative safety of BDC loans. Overall, the simultaneous increase in both the quantity and price of bank credit to BDCs is not driven by banks' capital or liquidity constraints, but by strong credit demand from BDCs seeking profitable investment opportunities.

### 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 predominantly obtain additional credit through renegotiation. Column (2) shows that loan commitments to BDCs grew by 3.6 (=4.7-1.1) percentage points more than those to other borrowers 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.<sup>27</sup> These patterns align

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<sup>26</sup>Unlike hold-to-maturity securities, AFS securities can be readily sold to raise liquidity and offset negative net-worth shocks.

<sup>27</sup>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.

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 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 combined with a favorable risk profile is consistent with banks' market power in the BDC lending market, as documented in Section 2.2. The high concentration of bank credit to BDCs—where a few large banks dominate lending relationships—suggests that BDCs borrow in a market with limited lender competition. Our evidence further shows that bank–BDC relationships are highly persistent and that BDCs face meaningful switching costs when replacing bank lenders. Such stickiness likely reflects relationship-specific information and contractual frictions that limit BDCs' ability to easily substitute among banks. During periods of elevated loan demand, such as monetary tightening, these frictions allow banks to exercise pricing power and extract rents, contributing to the observed rate premium. This dynamic mirrors the “upstream market power” mechanism identified by Jiang (2023) in the mortgage market, where informational frictions in warehouse lending enable banks to charge higher spreads to shadow banks. In the BDC context, this specialized and concentrated funding structure enhances banks' ability to balance profitability and risk, reinforcing their role as pivotal upstream financiers in the private-credit ecosystem.

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 to Firms 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 firms that borrow from both types of lenders, which we refer to as “overlapping borrowers.” While banks and BDCs do not lend to identical borrower bases, the overlap between their borrowers is economically substantial. Among all firms in the BDC Collateral dataset, 39% also appear in the Y-14 data at some point, indicating that roughly two-fifths of private-credit borrowers have relied on banks for financing at some stage. When we restrict the definition of overlap to include firms that have a bank loan within a five-year window of receiving private credit, the overlap rate shows an increasing trend over time (Appendix Figure A.5).<sup>28</sup> These patterns highlight the growing integration of bank and BDC lending and their role in closely connected segments of the corporate credit market.

For our regression analysis, we focus on firms that simultaneously hold both bank loan commitments and BDC credit in the same quarter, as this is required to isolate pricing and quantity differences within borrower-time pairs, following a framework similar to Khwaja and Mian (2008) and Chodorow-Reich (2014). This restriction yields a sample of about 4,800 overlapping borrowers. Appendix Table A.17 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. Because borrowers may increasingly prefer more permanent forms of financing—such as term

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<sup>28</sup>The temporary drop in 2020 reflects elevated drawdowns and subsequent repayments of bank loans for liquidity relief during the COVID-19 shock.



loans—during periods of tightening, it is crucial 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:

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

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*  $\times$  *year-quarter*  $\times$  *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.<sup>29</sup> Firms increase their utilization of BDC loans relative to bank loans during tightening, consistent with rising demand for private credit and BDCs' expansion of loan supply financed by additional bank borrowing.

**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). A back-of-the-envelope calculation implies that a 100-bp increase in the federal funds rate translates into roughly a 50-bp rise in private-credit borrowing costs, combining the effects of banks' repricing of BDC loans and BDCs' subsequent pass-through to firms. 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 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.<sup>30</sup> To test this, we re-estimate Eq. (2) by dividing overlapping borrowers into those likely constrained in bank

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<sup>29</sup>We use utilized amounts rather than commitments because BDC filings reports only utilized amounts, even though Y-14 provides both.

<sup>30</sup>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.

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 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.<sup>31</sup> 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

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<sup>31</sup>See [this Fitch Ratings article](#) on the rising trends of PIK features in private 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 expect these BDCs to increase their loan supply while charging higher rates, 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 financials. This combined dataset enables us to trace the full intermediation chain—from banks to BDCs to firms—and examine how monetary policy propagates through it.

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 reliance on bank credit. We estimate the following model:

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

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,  $\beta_1$ , 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 on  $BankLoanExpenseShare_{i,t} \times MP_t$  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.<sup>32</sup>

The estimated effect is economically significant. A BDC with a one-standard-deviation higher *BankLoanExpenseShare* (0.48) expands loan supply by 20.5% ( $0.48 \times 0.428$ ) and raises borrowing costs by 15 basis points ( $0.48 \times 0.313$ ) 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 loans while increasing lending where rates remain attractive.

An important indicator of banks' funding costs is their deposit beta—the sensitivity of deposit rates to changes in the federal funds rate (Drechsler et al., 2017). Banks with higher deposit betas face greater funding cost pressures and are likely to pass them on to BDCs, which then transmit these higher costs to their own borrowers. To test this channel, we use bank-level deposit betas from Drechsler et al. (2017) for Y-14 banks and construct a BDC-quarter level variable, *BankDepositBeta<sub>i,t</sub>*, as the weighted average of lending banks' deposit betas, where weights are each bank's utilized loan exposure to the BDC. A higher *BankDepositBeta<sub>i,t</sub>* thus indicates that a BDC borrows more heavily from banks with greater deposit-rate sensitivity and higher funding costs. In Columns (5)–(6) of Table 8, where the dependent variable is loan interest rate, the coefficients on the triple interaction term *BankDepositBeta*  $\times$  *BankLoanExpenseShare*  $\times$  *MP* are positive and significant, consistent with the pass-through of deposit funding costs from banks to BDCs and ultimately to firms.

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 relationships are relatively stable and unlikely to be driven by short-term credit decisions. Additionally, reliance on bank funding at the intensive margin is likely shaped by market-wide conditions, particularly BDCs' ability to substitute between bonds and loans—a

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<sup>32</sup>Across all columns, the coefficient on *BankLoanExpenseShare* is negative and statistically significant, suggesting that, under normal conditions (i.e., absent policy tightening), greater reliance on bank debt is associated with smaller loan amounts (Columns 1–2) and lower interest rates (Columns 3–4). This suggests bank-dependent BDCs may pursue more conservative lending strategies or favor lower-risk pricing.

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. The additional evidence on deposit betas reinforces this mechanism, showing that higher bank funding costs are systematically passed through to BDCs and, in turn, to firms. These findings underscore the importance of nonbank lenders and their funding structures in shaping monetary policy transmission through the credit chain.

## 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.<sup>33</sup> 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.17 compares overlapping borrowers with high and low BDC reliance to non-overlapping borrowers (those in Y-14 that do not hold BDC credit). High-

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<sup>33</sup>To maximize sample size, we relax our definition of overlapping borrowers by including firms 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.

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 also have fewer tangible assets than non-overlapping borrowers, which may limit their access to bank credit.

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

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

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*  $\times$  *External Credit Rating* fixed effects to absorb time-varying industry conditions and credit risk. External credit ratings are derived from banks' concordance maps from their internal ratings to a common S&P-like rating scale.<sup>34</sup>

Table 9 reports our results. Firms with high BDC reliance increased capital expenditures by 1.4% during tightening—an economically significant effect relative to the 2.0% sample mean (Table A.17). These firms also exhibited stronger asset and sales growth, though profitability declined, suggesting that increased investment and growth did not immediately translate into improved earnings. Moreover, BDC-reliant firms experienced a 30% lower interest coverage ratio during tightening relative to the sample mean, indicating higher interest expenses and weakening debt-service capacity.<sup>35</sup>

Overall, these results demonstrate that the quantity-price tradeoff in private credit provision has economically meaningful real consequences at the firm level: BDC-reliant borrowers achieve greater investment and growth but face heightened financial strain from higher borrowing costs on BDC loans.

<sup>34</sup>The mapping is based on the probability of default (PD). For example, if loans rated “3” by Bank 1 and “b5” by Bank 2 have similar PDs and fall within the PD range of publicly rated A (“single A”) loans, both would be mapped to an equivalent external rating of A. Although bank-internal credit ratings used in our baseline analysis are more granular, they are bank-specific and therefore unsuitable for firm-level regressions.

<sup>35</sup>Unreported tests confirm higher ratios of interest expense to lagged sales for BDC-reliant borrowers during tightening, suggesting the decline in interest coverage is driven by rising borrowing costs.



**Which firms switch from bank to BDC credit?** We also document meaningful lender switching among overlapping borrowers. During tightening, these firms substitute bank credit with BDC credit, consistent with a genuine elongation of the intermediation chain rather than a mere compositional shift. 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.<sup>36</sup> 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.

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<sup>36</sup>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.2–A.5](#) confirm that our main results are largely robust with these monetary policy shocks.

**Other Monetary Policy Tightening Cycles** Our economic narrative primarily focuses on the 2022 monetary tightening due to its unprecedented speed, the magnitude of rate hikes, and the accompanying slowdown in bank credit growth. The only other tightening cycle within our sample period (2012Q3–2023Q4) is the 2015–2018 cycle, which spanned from 2015Q4 to 2018Q4. To test the generalizability of our findings, we conducted an exercise using a dummy variable for the 2015 tightening cycle.

Appendix Table [A.6](#) 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 mech-

anism: 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.7–A.8 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.9 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 three robustness tests to assess whether our findings hold across different loan types.

First, a potential concern is that the observed differences between loans to BDCs and non-BDC borrowers could be mechanically driven by differences in loan type composition. Specifically, BDCs rely more heavily on credit lines, whereas non-BDC borrowers

obtain a larger share of term loans. To address this concern, we augment our baseline specification in Table 3 by including an interaction term between *CreditLine* and *MP*, allowing for potentially different sensitivities across loan types. As in Appendix Table A.10, our baseline results are largely unchanged, confirming that the stronger lending and higher rates for BDCs during tightening are not driven by differences in loan structure. Moreover, the results are robust when we restrict the sample to credit lines only (untabulated), further ruling out the possibility that our findings are an artifact of BDCs' greater use of credit lines.

Second, 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.11 confirms that, across various specifications, BDC loan utilization remains higher than that of non-BDCs during monetary tightening, supporting our main results.

Third, 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.12, 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.<sup>37</sup> With limited access to capital markets, private BDCs rely more on bank credit lines to seize investment opportunities. Fee structures may also impact bank financing demand. Public BDCs typically charge higher performance fees than private BDCs (Turner, 2019). Thus, despite having access to dry powder, private BDCs may use bank credit lines strategically—not just to fund investments but to enhance performance—depending on cash flow timing (Albertus and Denes, 2024).

To test whether our baseline findings on bank lending to BDCs (Tables 3 and 5) hold for both private and public BDCs, we re-estimate Eq. (1) on split samples. Appendix Tables A.13 (using *Tightening* as the monetary stance measure) and A.14 (using  $\Delta FF_t$ ) present the results. Across specifications, our key findings remain largely consistent for both BDC types. While coefficient estimates in Table A.14 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.15 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 to 1 if a BDC’s bank loan utilization rate is in the top quartile of the sample distribution,

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<sup>37</sup>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.

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.16 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.<sup>38</sup>

We leverage a unique feature of the data that identifies the lead lender for each loan

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<sup>38</sup>This data is sourced from an anonymous third-party valuation firm that provides loan appraisals for private credit managers.

based on actual credit agreements.<sup>39</sup> 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.18).

Our regression results in Table A.18 shows that firms exclusively borrowing from private credit managers experience stronger growth in assets and sales during the 2022 tightening 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.<sup>40</sup>

## 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

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<sup>39</sup>About two-thirds of the loans were originated by private credit managers, with the remainder consisting of bank-originated loans syndicated to them.

<sup>40</sup>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.



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 provide important insight on how future policy changes might propagate through increasingly complex intermediation chains.

Looking ahead, our study suggests several avenues for further research. First, while we focus on a period of pronounced monetary tightening in 2022, exploring whether these transmission channels behave symmetrically during easing cycles would offer a more complete picture of the broader macroeconomic implications. Second, investigating how heterogeneity among nonbanks—such as varying funding structures, risk profiles, and regulatory frameworks—shapes their role in monetary policy transmission could yield important policy insights. As nonbank lending grows and evolves, understanding these dynamics will be essential for both researchers and policymakers. Finally, as BDCs primarily serve larger and sponsor-backed firms, the shift from direct to indirect credit during tightening may have distributional consequences for smaller, bank-dependent borrowers—a channel warranting future research.

## References

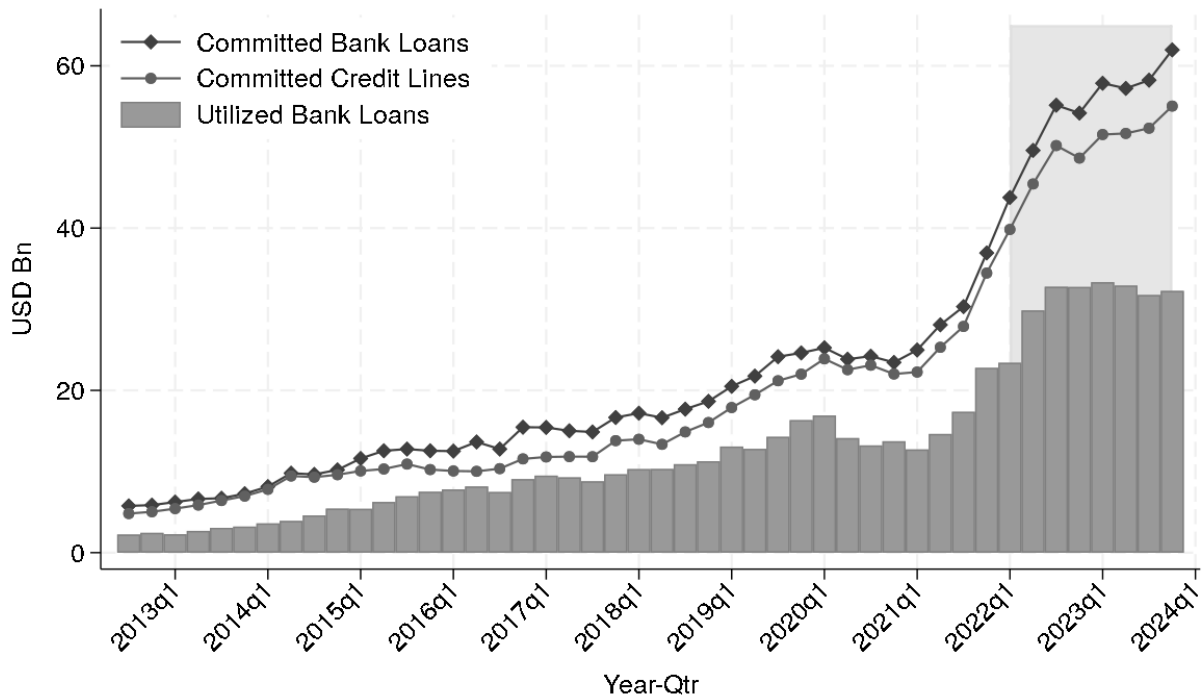
- Acharya, Viral V, Manasa Gopal, Maximilian Jager, and Sascha Steffen**, “Shadow Always Touches the Feet: Implications of Bank Credit Lines to Non-Bank Financial Intermediaries,” *Available at SSRN 4847858*, 2024.
- , **Nicola Cetorelli, and Bruce Tuckman**, “Where Do Banks End and NBFIs Begin?,” Technical 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-Urbe**, “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, Ben S and Alan S Blinder**, “of Monetary Transmission,” *The American Economic Review*, 1992, 82 (4), 901–921.
- Blickle, Kristian, Quirin Fleckenstein, Sebastian Hillenbrand, and Anthony Saunders**, “The myth of the lead arranger’s share,” *FRB of New York Staff Report*, 2022, (922).
- 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 Mislav, 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.

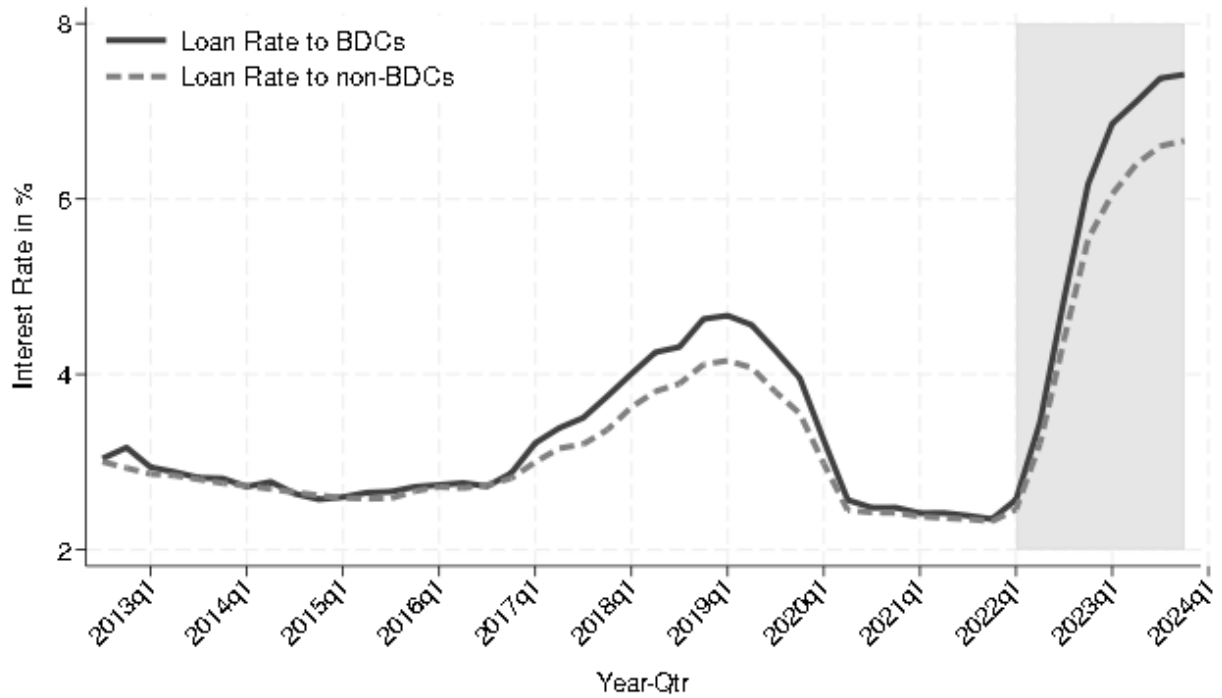
- Kashyap, Anil K and Jeremy C Stein**, “What do a million observations on banks say about the transmission of monetary policy?,” *American Economic Review*, 2000, 90 (3), 407–428.
- Kashyap, Anil K., Jeremy C. Stein, and David W. Wilcox**, “Monetary Policy and Credit Conditions: Evidence from the Composition 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.*

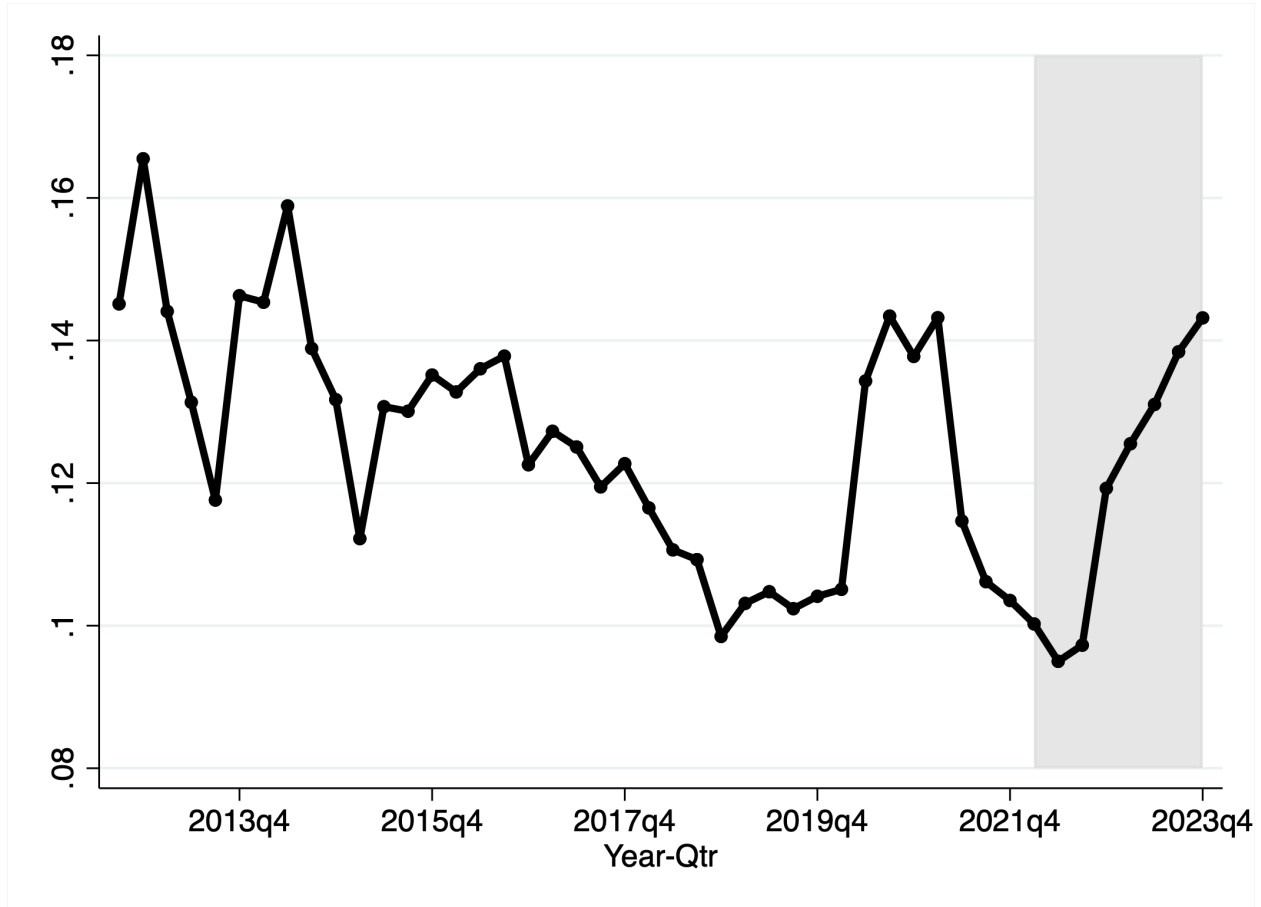
Figure 2. Interest Rate on Bank Loans: BDCs versus non-BDCs



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.

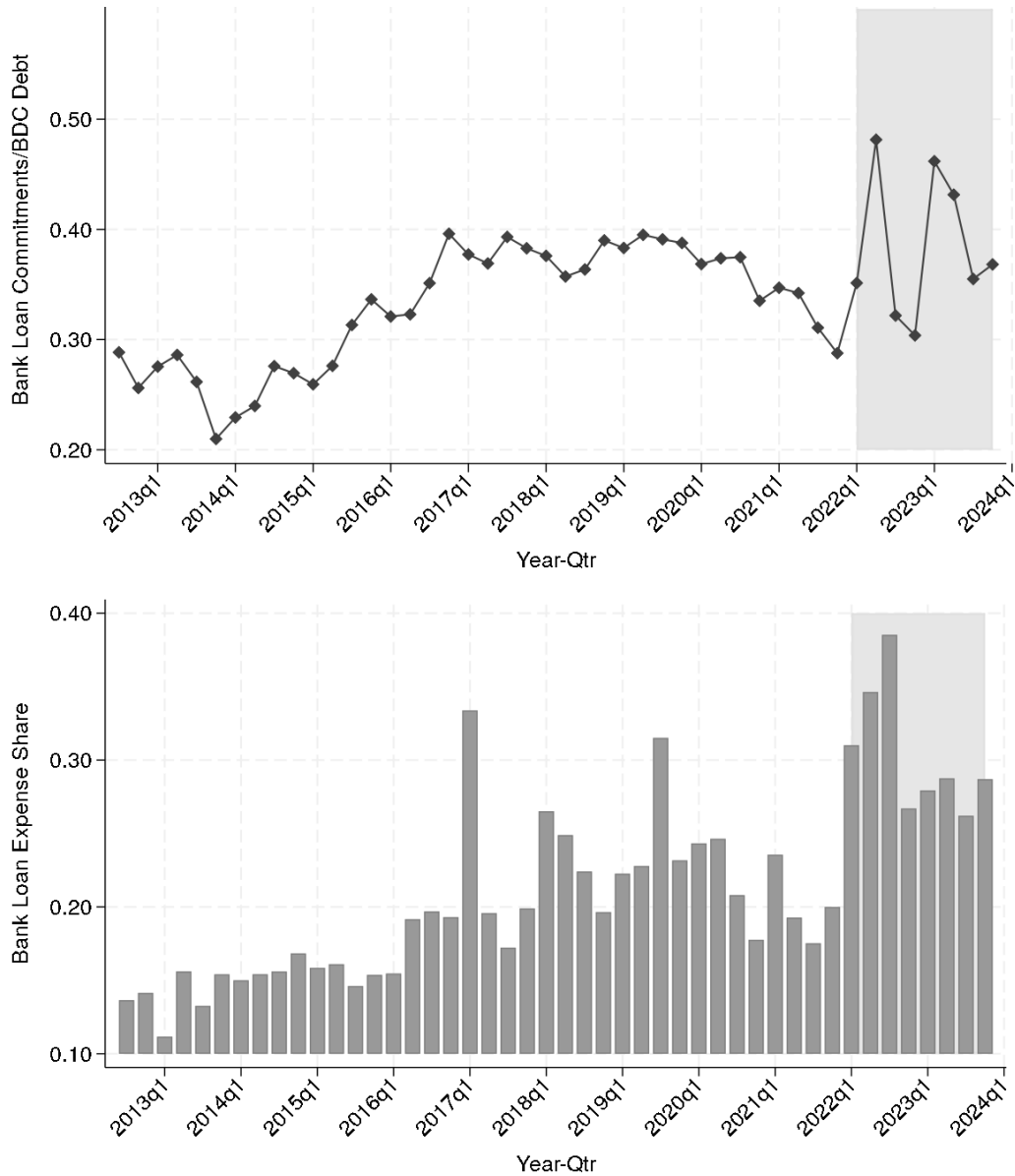


Figure 3. Fraction of BDC loans with PIK spread



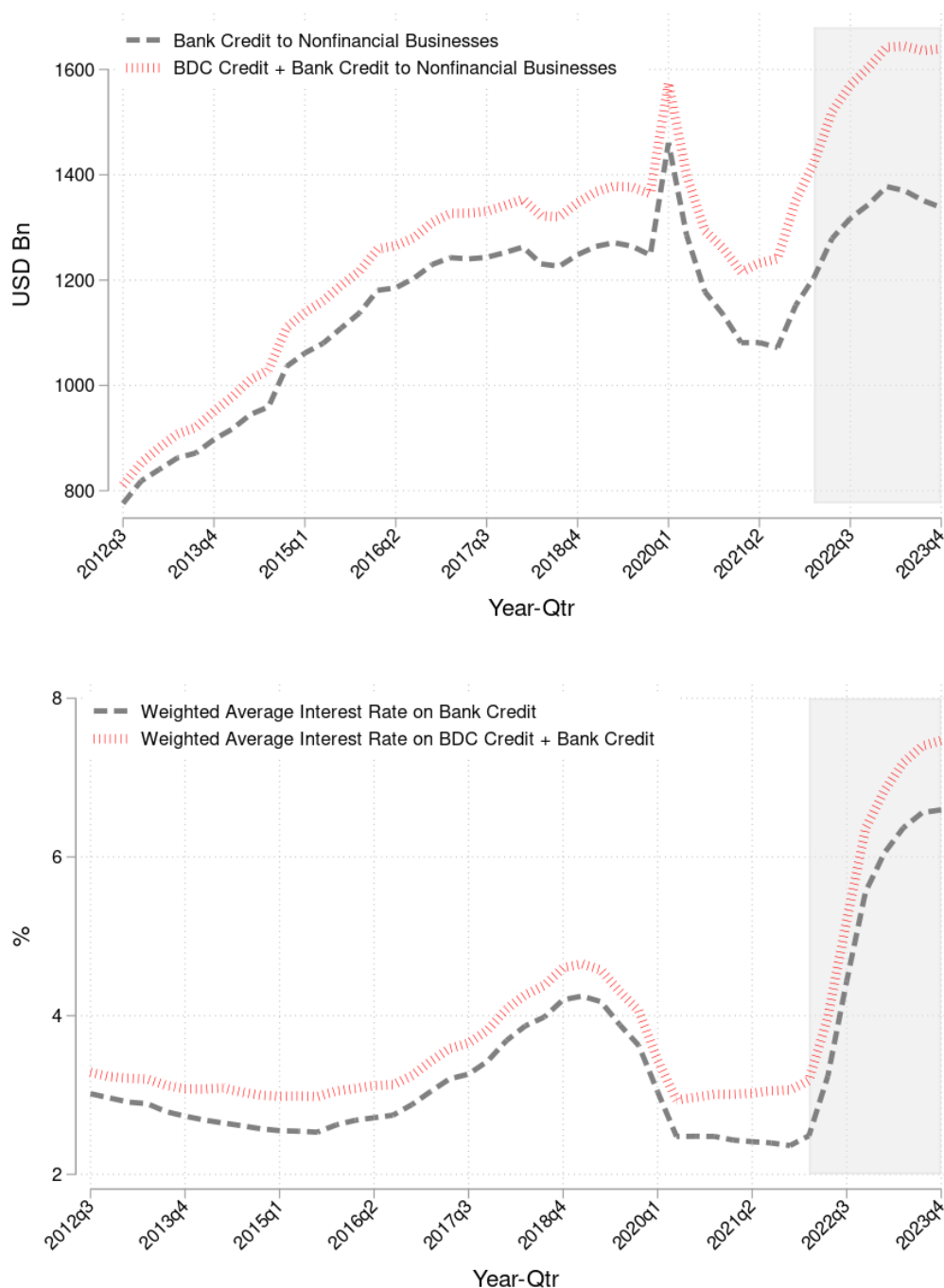
Notes: This figure plots the fraction of BDC loans with a non-zero payment-in-kind (PIK) spread from 2012Q3 to 2023Q4, weighted by loan amount. PIK allows borrowers to defer interest payments until maturity, typically in exchange for higher interest rates, providing borrowers with greater flexibility 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
$\Delta \text{Log}(\text{Loan})$	7,232	0.01	0.31	0.00
1×(First Lien Senior Secured)	10,197	0.92	0.27	1.00
1×(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
$\Delta \text{Log}(\text{Loan})$	5,290,219	-0.00	0.28	-0.00
1×(First Lien Senior Secured)	7,991,557	0.84	0.37	1.00
1×(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.  $\Delta \text{Log}(\text{Loan})$  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
1 × (Nonaccrual Loan)	460,170	0.03	0.16	0.00
1 × (Borrower Used PIK Option)	442,130	0.09	0.29	0.00
1 × (First Lien Debt)	460,192	0.83	0.37	1.00
1 × (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-Accrual) 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

	$\Delta \text{Log Loan}$	Utilization	Interest Rate	$\Delta \text{Log Loan}$	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times \text{Tightening}$	0.011** (0.004)	0.142*** (0.027)	0.009*** (0.002)			
$BDC \times \Delta FF$				0.709* (0.400)	9.372*** (2.154)	0.532*** (0.112)
$BDC$	0.001 (0.003)	0.044** (0.019)	0.002** (0.001)	0.003 (0.003)	0.071*** (0.017)	0.004*** (0.001)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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.  $\Delta FF$  is changes in the effective federal funds rate. BDC is a dummy equal to 1 if the borrower is a BDC, and 0 otherwise.  $\Delta \text{Log Loan}$  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  $\times$  borrower and YearQtr level.

Table 4. The Renegotiation Channel: panel A

Panel A: Increases in Credit Line Limits by Banks

$Y_{i,b,t} : \Delta \text{Log Loan}$	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times \text{Tightening}$	0.012** (0.005)	0.047*** (0.013)	-0.622 (0.382)			
$BDC \times \Delta FF$				0.810** (0.381)	2.648*** (0.925)	-28.915*** (8.621)
$BDC$	0.001 (0.003)	-0.011 (0.008)	0.483 (0.376)	0.004 (0.003)	0.002 (0.007)	0.159 (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.  $\Delta FF$  is changes in the effective federal funds rate. BDC is an dummy equal to 1 if the borrower is a BDC, and 0 otherwise.  $\Delta \text{Log Loan}$  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

$Y_{i,b,t} : \Delta \text{ Log Credit Line Utilization}$	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times \text{Tightening}$	0.113* (0.061)	0.105* (0.057)	0.266*** (0.080)			
$BDC \times \Delta FF$				7.810** (3.587)	5.853 (3.823)	15.883** (5.989)
$BDC$	0.038 (0.035)	0.036 (0.035)	0.042 (0.052)	0.059* (0.032)	0.058* (0.031)	0.109** (0.046)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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.  $\Delta FF$  is changes in the effective federal funds rate. BDC is an dummy equal to 1 if the borrower is a BDC, and 0 otherwise.  $\Delta \text{ Log (CL Utilization)}$  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  $\times$  borrower and YearQtr level.

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

	1st Lien Senior Secured		Collateralized		Loss Given Default		Probability of Default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>BDC × Tightening</i>	0.103*** (0.020)		0.103*** (0.020)		-0.027** (0.011)		0.002 (0.002)	
<i>BDC × ΔFF</i>		5.910*** (1.534)		6.227*** (1.436)		-2.397*** (0.593)		0.154 (0.118)
<i>BDC</i>	0.282*** (0.017)	0.304*** (0.016)	0.284*** (0.017)	0.305*** (0.017)	-0.083*** (0.013)	-0.087*** (0.012)	0.002*** (0.001)	0.002*** (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.  $\Delta FF$  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  $\times$  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*** (0.116)	0.516*** (0.117)			0.252*** (0.093)	0.251*** (0.077)		
$BDC \times \Delta FF$			37.646*** (8.238)	37.156*** (8.342)			15.094*** (4.978)	14.957*** (4.945)
$BDC$	0.949*** (0.096)	0.978*** (0.097)	1.107*** (0.088)	1.135*** (0.087)	-0.378*** (0.080)	-0.372*** (0.064)	-0.294*** (0.066)	-0.288*** (0.067)
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm $\times$ YrQtr $\times$ 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*** (0.210)	0.380*** (0.128)			0.319*** (0.087)	0.204* (0.115)		
$BDC \times \Delta FF$			62.668*** (15.991)	23.576*** (7.847)			16.107*** (5.399)	12.960* (6.455)
$BDC$	1.074*** (0.131)	0.896*** (0.113)	1.279*** (0.125)	1.041*** (0.094)	-0.549*** (0.070)	-0.325*** (0.100)	-0.464*** (0.062)	-0.248*** (0.080)
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm $\times$ YrQtr $\times$ 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
$H_0 : \text{Constrained} - \text{Unconstrained} > 0$	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.  $H_0 : \text{Constrained} - \text{Unconstrained} > 0$  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*** (0.154)	0.291* (0.164)			0.263** (0.117)	0.242** (0.103)		
$BDC \times \Delta FF$			51.413*** (10.217)	14.192 (10.267)			18.411*** (6.345)	9.078 (5.986)
$BDC$	0.983*** (0.115)	0.992*** (0.153)	1.171*** (0.100)	1.098*** (0.131)	-0.369*** (0.096)	-0.463*** (0.087)	-0.290*** (0.076)	-0.369*** (0.083)
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm $\times$ YrQtr $\times$ 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
$H_0 : \text{Constrained} - \text{Unconstrained} > 0$	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.  $H_0 : \text{Constrained} - \text{Unconstrained} > 0$  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**

	<b>1 × (Borrower Used PIK Option)</b>			
	(1)	(2)	(3)	(4)
<b>1 × (Nonaccrual Loan) × Tightening</b>	0.120*** (0.032)	0.096** (0.044)		
<b>1 × (Nonaccrual Loan) × ΔFF</b>			6.694*** (2.046)	5.081* (2.552)
<b>1 × (Nonaccrual Loan)</b>	0.127*** (0.019)	0.104*** (0.035)	0.153*** (0.019)	0.142*** (0.029)
Loan Controls	Y	Y	Y	Y
Firm FE	Y		Y	
Firm × 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, **1 × (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. **1 × (Nonaccrual Loan)** is 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)	(5)	(6)
<i>BankLoanExpenseShare</i> × <i>Tightening</i>	0.428*** (0.121)		0.313*** (0.073)		-0.948** (0.446)	
<i>BankLoanExpenseShare</i> × $\Delta FF$		21.553** (10.466)		9.056** (3.881)		-50.347*** (17.196)
<i>BankLoanExpenseShare</i>	-0.442*** (0.126)	-0.247*** (0.0879)	-0.231*** (0.0633)	-0.0857** (0.0390)	0.497 (0.427)	-0.172 (0.181)
<i>BankLoanExpenseShare</i> × <i>Tightening</i> × <i>BankDepositBeta</i>					2.499** (1.009)	
<i>BankLoanExpenseShare</i> × $\Delta FF$ × <i>BankDepositBeta</i>						106.529*** (38.311)
Controls	Y	Y	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y	Y	Y
R-squared	0.501	0.501	0.559	0.559	0.555	0.554
N	353,559	353,559	341,009	341,009	261,946	261,946

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

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 (natural log of the loan's face value in dollars) in columns (1)–(2) and Interest Rate (interest rate on a given loan in percentage points) in columns (3)–(6). *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.  $\Delta FF$  is changes in the effective federal funds rate, expressed as a decimal. Columns (5)–(6) augment the specification with a triple interaction that includes a BDC-level measure *BankDepositBeta*, constructed as the weighted average of each BDC's lending banks' deposit betas from [Drechsler et al. \(2017\)](#), using utilization amounts as weights. Control variables include BDC total assets, loan maturity, and a non-accrual indicator for each loan. Columns (5)–(6) also include all lower-order interactions and the main term for *BankDepositBeta*. Sample size is smaller in Columns (5)–(6) because these estimations require BDCs to have strictly positive bank loans, whereas Columns (1)–(4) assign a value of zero to BDCs that never appear in Y-14. 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)
<i>High BDC Reliance</i> × <i>Tightening</i>	0.014** (0.007)	0.147*** (0.052)	0.047* (0.028)	-0.034*** (0.008)	-1.614** (0.684)
<i>High BDC Reliance</i>	-0.005 (0.004)	-0.136*** (0.027)	-0.050*** (0.019)	-0.000 (0.005)	0.352 (0.365)
Lagged Firm Controls	Y	Y	Y	Y	Y
3-Digit Ind × Year × Rating FE	Y	Y	Y	Y	Y
R-squared	0.267	0.266	0.303	0.495	0.416
N	3,845	3,811	3,806	3,881	3,855

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

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. Rating refers to firm-level credit ratings mapped from bank's internal ratings to an S&P-like letter-grade scale for comparability across firms. Standard errors are clustered at the borrower level.

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

	<i>Switchers from Bank Credit to BDC Credit</i>	<i>Credit-Squeezed by Banks and BDCs</i>	<i>Bank-Favored</i>
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.
- $\Delta \text{Log}(\text{Loan})$ : Log quarterly change in total loan commitment at the bank-borrower level.
- $1 \times (\text{First Lien Senior Secured})$ : 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.
- $1 \times (\text{Collateralized})$ : 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.
- $1 \times (\text{Term})$ : 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.
- $1 \times (ROA < 0)$ : Dummy variable equal to 1 if EBITDA/ROA is negative for the current year.
- *Credit Rating*: Bank's internal credit rating, defined at the borrower level, bank-specific and time-varying, capturing the bank's ex-ante assessment of credit risk.
- *External Credit Rating*: Borrower-level, time-varying credit ratings. Y-14 banks are required to submit concordance maps from their internal ratings to a common S&P-like scale based on the probability of default. For example, if loans rated "3" by Bank 1 and "b5" by Bank 2 have similar PDs and fall within the PD range of publicly rated A ("single A") loans, both would be mapped to an equivalent external rating of A.
- *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.
- $1 \times (\text{Term})$ : 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).
- $1 \times (\text{Non-accrual})$ : Indicator variable equal to 1 if the given loan is reported as non-accruing in a given quarter.
- $1 \times (\text{Borrower Used PIK Option})$ : 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 Deposit Beta*: A BDC-quarter-level variable defined as the weighted average of lending banks' deposit betas, where the weights are each bank's utilized loan exposure to a BDC in a given quarter.
- *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).
- $\Delta FF$ : 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, Minoi 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.
- When using asset growth and sales growth in regressions, these variables are further trimmed at the 1 and 99 percent level to remove extreme values.
- 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 (Newtek Business Services) 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



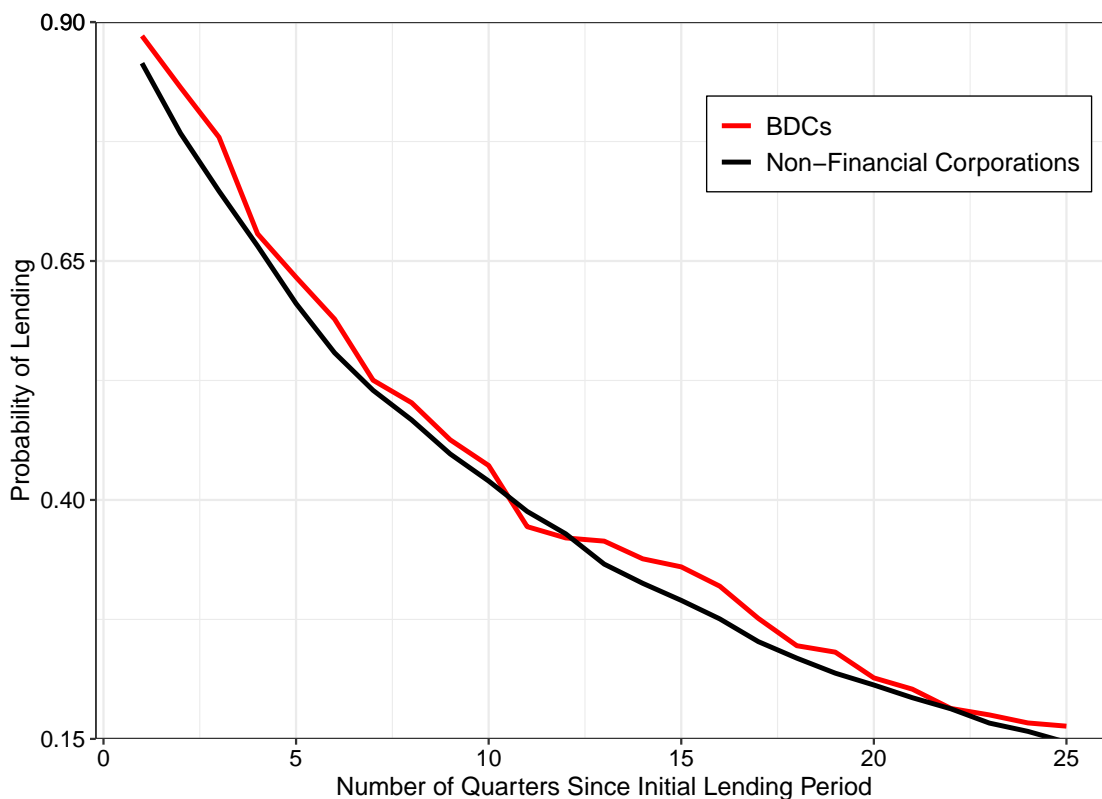
differences between the two groups are not statistically significant, even at the 10% level (assuming unequal variances).

### 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

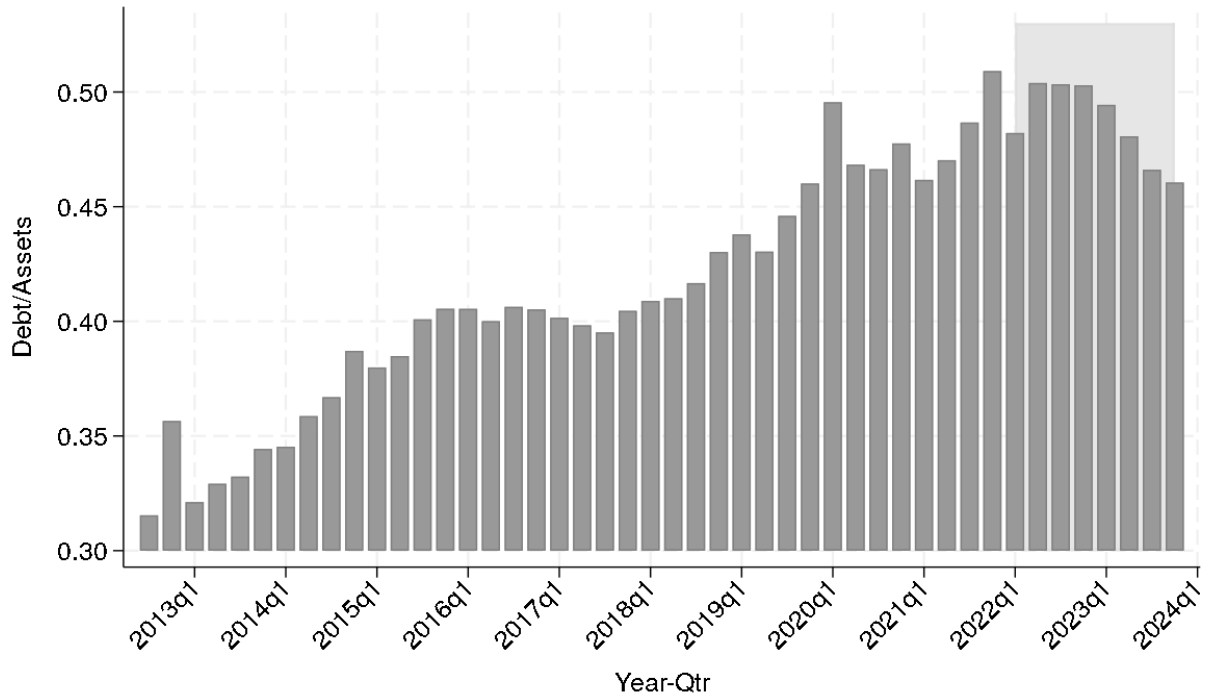
## A.4 Additional Figures

Figure A.1. Persistent Bank-Borrower Relationships



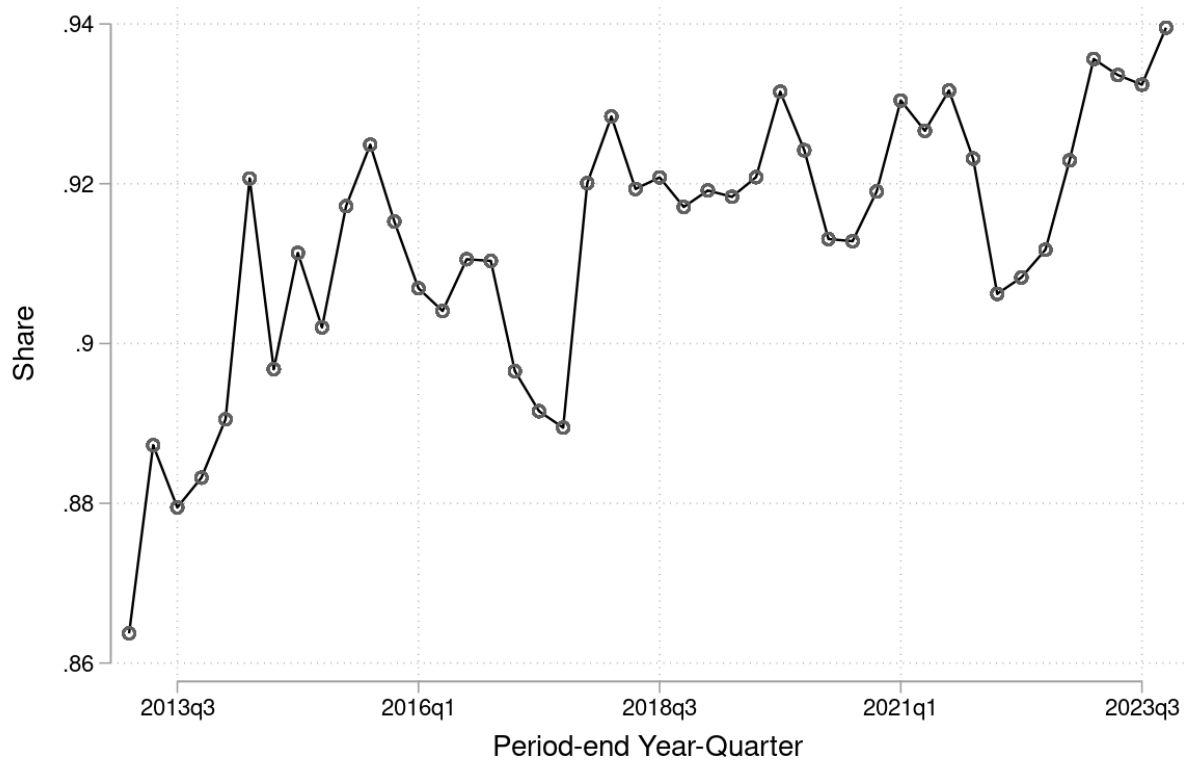
Notes: This figure plots the likelihood of maintaining a bank-BDC lending relationship in quarters 1 to 25, conditional on having such a relationship in quarter 0. The sample includes all possible bank-BDC pairs in the data. To compute the conditional probability, we identify the first quarter of each lending relationship (defined as quarter 0) and then track these matched pairs over the subsequent 25 quarters. The conditional probability in quarter  $t$  is the share of bank-BDC pairs that had a lending relationship in quarter 0 and still have one after  $t$  quarters. As a benchmark, the same conditional probability is plotted for all bank-nonfinancial firm pairs.

Figure A.2. BDC Leverage



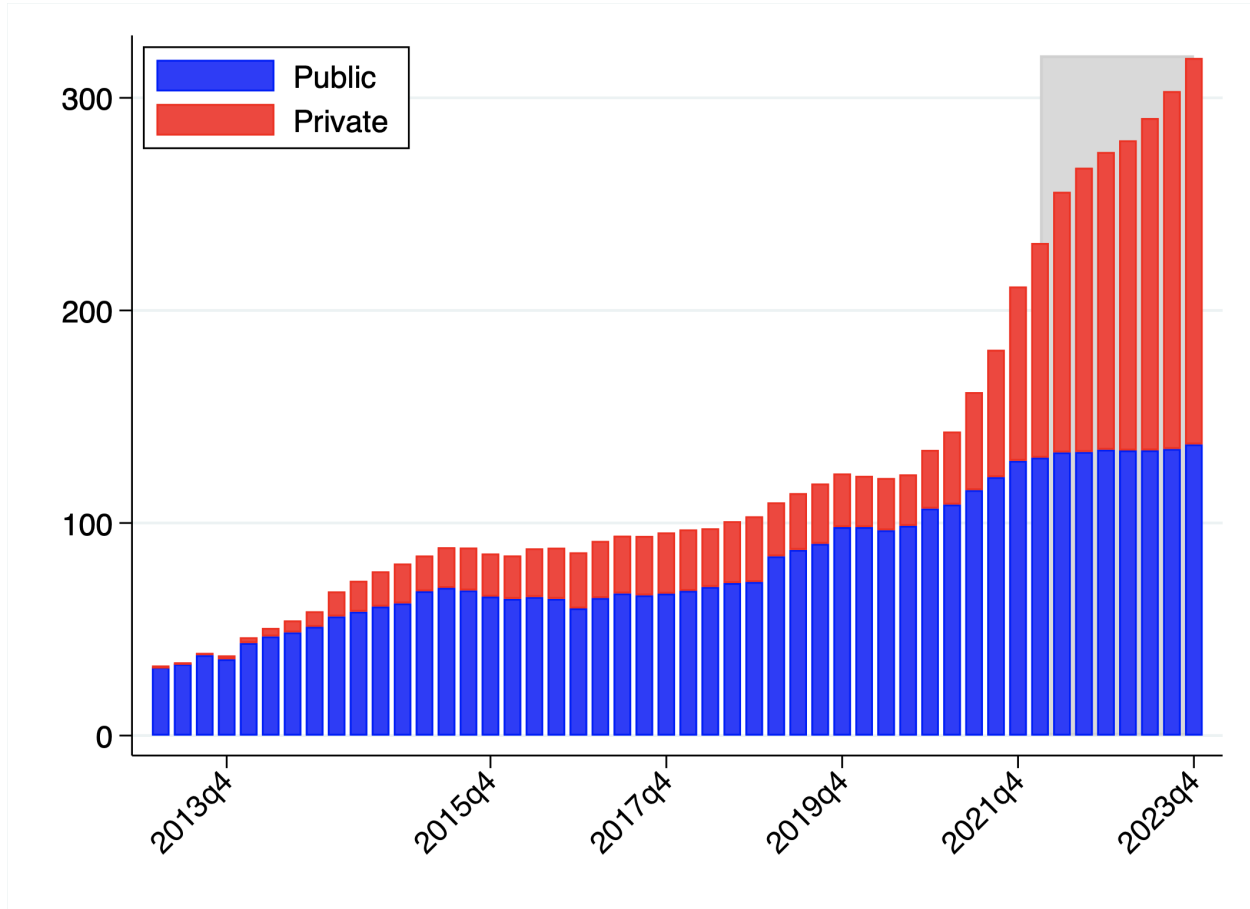
Notes: This figure plots the time series of the average BDC Leverage (Debt/Asset) weighted by BDC assets. The sample period is 2012Q3–2023Q4. The sample includes 190 BDCs with available data.

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



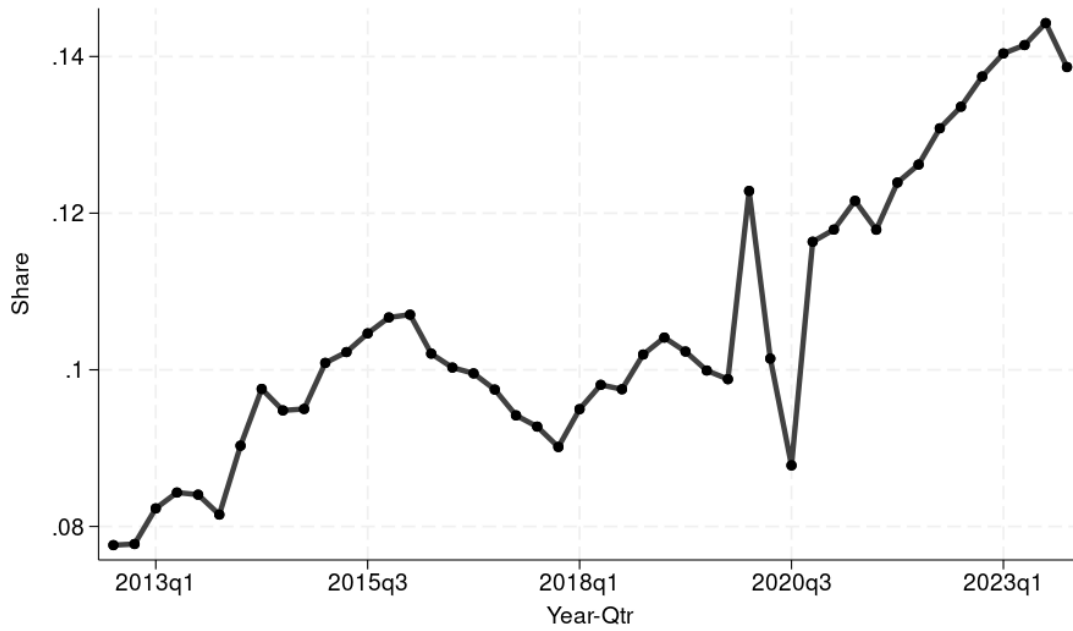
Notes: This figure plots the share of total BDC credit provided by Y-14 bank-reliant BDCs. Credit amount refers to the total par value of loans at a given time for each BDC. Bank-reliant BDCs are those with a non-zero loan commitment from a bank. The sample period spans 2012Q3 to 2023Q4, with 142 unique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

Figure A.4. 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.5. Share of Bank Loans Held by Overlapping Borrowers



Notes: This figure plots the share of total bank loan commitments to middle-market firms that are held by overlapping borrowers. Overlapping borrowers are defined as firms that obtain both bank and private credit, though not necessarily in the same quarter. Middle-market firms are those with annual sales between USD 10 million and USD 1 billion. To remain conservative, firms with missing financial data are also included in the middle-market definition.

## A.5 Additional Tables

Table A.1. Robustness to Table 3: are results driven by bank-side supply constraints?

	Exclude capital-constrained banks			Exclude liquidity-constrained banks		
	$\Delta \text{Log Loan}$	Utilization	Interest Rate	$\Delta \text{Log Loan}$	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
<i>BDC <math>\times</math> Tightening</i>	0.008* (0.005)	0.137*** (0.029)	0.009*** (0.002)	0.009* (0.005)	0.127*** (0.029)	0.010*** (0.002)
<i>BDC</i>	0.001 (0.003)	0.051** (0.021)	0.001 (0.001)	0.001 (0.003)	0.042** (0.020)	0.002** (0.001)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.286	0.490	0.023	0.275	0.475
N	2,815,017	1,303,847	2,672,728	2,844,244	1,325,062	2,720,530

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

Notes: This table presents robustness checks for Table 3 by excluding financially constrained banks, following two definitions. Columns (1)–(3) exclude banks whose total capital-to-risk-weighted assets (RWA) ratio falls below the 25th percentile in a given quarter (“capital-constrained”). Columns (4)–(6) exclude banks whose available-for-sale (AFS) securities-to-RWA ratio falls below the 25th percentile (“liquidity-constrained”).

Table A.2. Robustness to Table 3 and Table 5: alternative monetary policy shocks

	$\Delta \text{Log Loan}$	Utilization	Interest Rate	1st Lien	Collateralized	LGD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Monetary Policy Shock from Jarociński and Karadi (2020)						
$BDC \times MPShocks$	0.090** (0.038)	0.573*** (0.200)	0.013 (0.013)	0.282** (0.135)	0.325** (0.133)	-0.093** (0.041)
$BDC$	0.005* (0.003)	0.088*** (0.018)	0.005*** (0)	0.314*** (0.017)	0.317*** (0.017)	-0.096*** (0.014)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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)						
$BDC \times MPShocks$	0.047*** (0.015)	0.294** (0.131)	0.007 (0.008)	0.146* (0.086)	0.178** (0.087)	-0.043*** (0.009)
$BDC$	0.004* (0.002)	0.085*** (0.018)	0.005*** (0)	0.313*** (0.017)	0.315*** (0.017)	-0.095*** (0.014)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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.3. Robustness to Table 6: alternative monetary policy shocks

	Interest Rate	Loan Amount
	(1)	(2)
Panel A: Monetary Policy Shock from Jarociński and Karadi (2020)		
<i>BDC × MP Shock</i>	1.909** (0.752)	1.687*** (0.439)
<i>BDC</i>	1.213*** (0.093)	-0.265*** (0.063)
R-squared	0.923	0.604
N	309,295	309,295
Panel B: Monetary Policy Shock from Bauer and Swanson (2023)		
<i>BDC × MP Shocks</i>	1.059*** (0.389)	0.836** (0.369)
<i>BDC</i>	1.209*** (0.092)	-0.267*** (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.4. Robustness to Table 7: alternative monetary policy shocks

	$1 \times (\text{Borrower Used PIK Option})$			
	(1)	(2)	(3)	(4)
$1 \times (\text{Nonaccrual Loan}) \times \text{Jarocinski-Karadi Shock}$	0.321** (0.157)	0.193 (0.191)		
$1 \times (\text{Nonaccrual Loan}) \times \text{Bauer-Swanson Shock}$			0.169** (0.074)	0.136* (0.072)
$1 \times (\text{Nonaccrual Loan})$	0.164*** (0.020)	0.151*** (0.031)	0.161*** (0.019)	0.150*** (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.5. Robustness to Table 8: alternative monetary policy shocks

	Loan Amount		Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)
<i>BankLoanExpenseShare</i> × <i>JarocinskiKaradi Shock</i>	1.985*** (0.668)		0.798** (0.353)		-1.496 (1.036)	
<i>BankLoanExpenseShare</i> × <i>BauerSwanson Shock</i>		0.612 (0.527)		0.448* (0.249)		-0.216 (0.518)
<i>BankLoanExpenseShare</i>	-0.305*** (0.075)	-0.234*** (0.081)	-0.105** (0.043)	-0.093** (0.043)	-0.070 (0.170)	-0.171 (0.160)
<i>BankLoanExpenseShare</i> × <i>JarocinskiKaradi Shock</i> × <i>BankDepositBeta</i>					4.393* (2.422)	
<i>BankLoanExpenseShare</i> × <i>BauerSwanson Shock</i> × <i>BankDepositBeta</i>						0.992 (1.536)
Controls	Y	Y	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y	Y	Y
R-squared	0.501	0.501	0.559	0.559	0.555	0.554
N	353,559	353,559	341,009	341,009	261,946	261,946

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

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.6. 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)
<i>BDC × 2015Tightening</i>	0.000352 (0.00693)	-0.0579* (0.0304)	-0.000112 (0.000804)	-0.0252* (0.0125)	-0.0244 (0.0191)	-0.0339* (0.0194)
<i>BDC</i>	0.00358 (0.00396)	0.0671*** (0.0240)	0.00466*** (0.000548)	-0.0837*** (0.0142)	0.293*** (0.0192)	0.297*** (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.7. Robustness to Table 3: including bank-borrower fixed effects

	$\Delta\text{Log Loan}$	Utilization	Interest Rate	$\Delta\text{Log Loan}$	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times \text{Tightening}$	0.018** (0.008)	0.089*** (0.026)	0.007*** (0.002)			
$BDC \times \Delta FF$				0.552 (0.383)	4.600*** (1.347)	0.325*** (0.081)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ YrQtr FE	Y	Y	Y	Y	Y	Y
Bank $\times$ 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.8. 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)
$BDC \times Tightening$	0.039*** (0.014)		0.039*** (0.013)		-0.012** (0.005)		-0.001 (0.001)	
$BDC \times \Delta FF$		1.826** (0.815)		2.150** (0.915)		-0.672*** (0.238)		-0.026 (0.081)
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ YrQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank $\times$ 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.9. Robustness to Table 3: alternative definitions of other borrowers

	$\Delta\text{Log Loan}$	Utilization	Interest Rate	$\Delta\text{Log Loan}$	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times \text{Tightening}$	0.011** (0.005)	0.141*** (0.027)	0.009*** (0.002)			
$BDC \times \Delta FF$				0.726* (0.409)	9.450*** (2.111)	0.542*** (0.114)
$BDC$	0.001 (0.003)	0.052*** (0.019)	0.002** (0.001)	0.003 (0.003)	0.079*** (0.017)	0.004*** (0.001)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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.10. Robustness to Table 3: controlling for BDCs' greater reliance on credit lines

	$\Delta\text{Log Loan}$	Utilization	Interest Rate	$\Delta\text{Log Loan}$	Utilization	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$BDC \times \text{Tightening}$	0.011** (0.004)	0.142*** (0.027)	0.005*** (0.001)			
$BDC \times \Delta FF$				0.619 (0.370)	9.308*** (2.203)	0.177*** (0.064)
$BDC$	0.001 (0.003)	0.044** (0.019)	0.003*** (0.001)	0.004 (0.003)	0.071*** (0.017)	0.005*** (0.001)
$\text{CreditLine} \times \text{Tightening}$	-0.001 (0.002)	-0.008 (0.008)	0.013*** (0.003)			
$\text{CreditLine} \times \Delta FF$				0.272* (0.150)	1.267 (1.153)	0.935*** (0.178)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ YrQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.028	0.286	0.497	0.028	0.286	0.490
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 robustness checks for Table 3 addressing the concern that BDCs rely more heavily on credit lines than other borrowers. The specification includes an interaction between CreditLine and the monetary policy variable (Tightening or  $\Delta FF$ ) to allow for differential sensitivities across loan types. CreditLine denotes the share of a firm's total bank loans that are credit lines. All fixed effects and controls are identical to the baseline.



Table A.11. Robustness to Table 3: utilization rate for all loan types

	Utilization Rate			
	(1)	(2)	(3)	(4)
$BDC \times Tightening$	0.108*** (0.024)	0.089*** (0.025)		
$BDC \times \Delta FF$			5.803** (2.687)	5.500** (2.171)
$BDC$	0.012 (0.020)	0.022 (0.021)	0.035* (0.020)	0.040** (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.12. Robustness to Table 5: restricting sample to existing credit lines

	1st Lien Senior Secured		Collateralized		Loss Given Default		Probability of Default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BDC \times Tightening$	0.107*** (0.021)		0.105*** (0.021)		-0.086*** (0.016)		0.005 (0.003)	
$BDC \times \Delta FF$		7.235*** (1.721)		6.937*** (1.645)		-5.625*** (1.215)		0.315 (0.202)
$BDC$	0.298*** (0.018)	0.318*** (0.019)	0.297*** (0.018)	0.316*** (0.018)	-0.036*** (0.007)	-0.053*** (0.009)	0.001 (0.001)	0.001 (0.001)
Lagged Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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.13. 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						
<i>BDC × Tightening</i>	0.010* (0.006)	0.143*** (0.028)	0.009*** (0.002)	-0.011 (0.013)	0.090*** (0.021)	0.086*** (0.021)
<i>BDC</i>	0.001 (0.004)	0.020 (0.020)	0.002* (0.001)	-0.096*** (0.018)	0.288*** (0.019)	0.291*** (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						
<i>BDC × Tightening</i>	0.009 (0.010)	0.092** (0.043)	0.009*** (0.001)	-0.039 (0.023)	0.138*** (0.039)	0.144*** (0.040)
<i>BDC</i>	0.004 (0.008)	0.127*** (0.031)	0.003*** (0.001)	-0.069*** (0.017)	0.260*** (0.034)	0.261*** (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.14. 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 (0.267)	8.373*** (2.164)	0.527*** (0.114)	-1.201*** (0.230)	4.344*** (1.463)	4.350*** (1.331)
$BDC$	0.004 (0.003)	0.043** (0.019)	0.003*** (0.001)	-0.097*** (0.018)	0.305*** (0.018)	0.306*** (0.019)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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** (0.942)	9.210*** (2.544)	0.497*** (0.117)	-3.625** (1.415)	8.872*** (2.673)	9.710*** (2.661)
$BDC$	0.003 (0.006)	0.147*** (0.024)	0.006*** (0.001)	-0.078*** (0.014)	0.302*** (0.029)	0.304*** (0.029)
Lagged Controls	Y	Y	Y	Y	Y	Y
Bank $\times$ Credit Rating $\times$ 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.15. Robustness to Table 8: alternative bank reliance measures

	Loan Amount		Interest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)
<i>High Bank Reliant</i> × <i>Tightening</i>	0.197** (0.0793)	0.234*** (0.0781)	0.326*** (0.0846)	0.285*** (0.0713)	-0.797* (0.419)	-0.763*** (0.243)
<i>High Bank Reliant</i>	-0.234*** (0.0653)	-0.162** (0.0769)	-0.0274 (0.0636)	-0.200*** (0.0599)	0.396 (0.281)	0.099 (0.209)
<i>High Bank Reliant</i> × <i>Tightening</i> × <i>Bank Deposit Beta</i>					2.461** (0.926)	1.928*** (0.426)
Controls	Y	Y	Y	Y	Y	Y
BDC FE	Y	Y	Y	Y	Y	Y
YrQtr FE	Y	Y	Y	Y	Y	Y
Loantype FE	Y	Y	Y	Y	Y	Y
R-squared	0.506	0.506	0.563	0.563	0.555	0.555
N	363,931	363,931	350,861	350,861	262,518	262,518

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

Notes: This table reports robustness tests for Table 8 using alternative measures for BDCs' reliance on banks. For Columns (1), (3) and (5) 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), (4) and (6) 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.16. Robustness to Table 8: alternative controls

	Loan Amount		Interest Rate	
	(1)	(2)	(3)	(4)
<i>BankLoanExpense</i> × <i>Tightening</i>	0.313*** (0.111)		0.427*** (0.114)	
<i>BankLoanExpense</i> × $\Delta FF$		21.880** (8.531)		7.724* (3.940)
<i>BankLoanExpense</i>	-0.487*** (0.146)	-0.266** (0.100)	-0.311*** (0.097)	-0.134** (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.17. Summary Statistics for Borrowers Financials**

Variable	Count	Mean	SD	Median
<i>Panel A: Overlapping Borrowers with Low BDC Reliance</i>				
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
$1 \times (ROA < 0)$	6,450	0.07	0.25	0.00
<i>Panel B: Overlapping Borrowers with High BDC Reliance</i>				
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
$1 \times (ROA < 0)$	2,813	0.19	0.39	0.00
<i>Panel C: Non Overlapping Borrowers</i>				
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
$1 \times (ROA < 0)$	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 financial data.

**Table A.18. Real Effects of BDC Credit during Tightening: external validity**

Panel A: Summary Statistics					
Variable	Count	Mean	SD	Median	
<i>Borrowers of Private Credit-Originated Loans</i>					
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	
<i>Borrowers of Bank-Originated Loans</i>					
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)
<i>PrivateCredit</i> ×	-0.001	0.059**	0.026***	0.008	0.230
<i>Tightening</i>	(0.001)	(0.024)	(0.006)	(0.004)	(0.131)
<i>PrivateCredit</i>	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.